MODELLING AND SYSTEMATIC ASSESSMENT OF MARITIME CONTAINER SUPPLY CHAIN RISKS

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A thesis submitted in partial fulfilment of the requirements of Liverpool John Moores University for the degree of Doctor of Philosophy

July 2018

Abstract

Maritime container supply chains (MCSCs) is exposed to various risks arising from both internal operations and the external environment, and the increasing complexity of the modern global logistics system makes the situation even worse, thus causing a significant challenge to the effective risk management of MCSCs. However, systematic studies on this topic are relatively few. In view of this, this study aims to explore and analyse various MCSC risks, develop suitable risk assessment methods, and evaluate the overall performance of MCSCs from a systematic perspective, so as to ensure the safety, reliability, and resilience of MCSCs.

This research starts with the identification and classification of all possible risk factors that may be involved in an MCSC based on a comprehensive literature review, and the research results are further validated through a Delphi expert survey. The identified risk factors are then analysed, screened, and assessed in detail. The novelty of this study lies not only on the risk assessment of MCSCs under an uncertain environment from a supply chain level but also on the consideration of the impact of risk condition of each individual MCSC on the overall performance of the entire container supply network.

The research results will provide useful insights and valuable information for both researchers and practitioners on the risk analysis and assessment of MCSCs, which is beneficial to different types of stakeholders involved in the maritime shipping industry. The work is also able to provide a theoretical foundation for risk-based decision making and shipping route optimisation in further work. Although the risk assessment methods are presented on the basis of the specific context in MCSCs, it is believed that, with domain-specific knowledge and data, they can also be tailored for a wide range of applications to evaluate the reliability and performance of other supply chain systems, especially where a high level of uncertainty is involved.

Acknowledgements

This thesis is the result of three years' work under the support of a Dual-PhD project between Liverpool John Moores University (LJMU) and Wuhan University of Technology (WUT), China. It has been a long journey, but I do not feel alone as I have been accompanied and supported by many wonderful people.

First and foremost I would like to thank my principal supervisor Professor Zaili Yang for his patient supervision, invaluable guidance, constant encouragement, and constructive technical suggestions throughout the duration of the research. More importantly, his enthusiasm and meticulous working attitude towards the research have impressed and inspired me a lot. I owe him lots of gratitude for what I have learnt from him. It is really my pleasure to be the student under his supervision. I would also like to thank my co-supervisors in LJMU, Dr Jun Ren and Dr Eduardo Blanco Davis, for the kind assistance that they offered me in gaining a better understanding of my research topic from the perspective of their specialist areas.

I owe special thanks to my supervisory board in China, Professor Xinping Yan and Professor Di Zhang at WUT, for their extraordinary support for my research. They also have offered me a great opportunity to be involved in the EU funded ENRICH project to advance my knowledge on risk management of maritime container supply chains and to attend international academic conferences to extend my network in the research community.

I would like to thank my friends whom I met in Liverpool, such as Dr Hani Alyami, Dr Min-Ho Ha, Dr Chaoyu Li, Dr Jing Shi, Dr Lei Wang, Dr Zhisen Yang, Dr Xiao Yang and others. I really enjoyed the time with them. Thanks are also given to members of Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, for their collaboration during the research.

This research has been supported and funded by various organisations including the European Commission (EC), WUT, and China Scholarship Council (CSC). I thank them for their financial assistance to me. I am also grateful for the Department of Maritime and Mechanical Engineering at LJMU for providing me with an excellent working environment during the period of the research in the UK.

I feel a deep sense of gratitude to my parents for their material and spiritual support in my academic pursuit in the UK. They have provided me with over twenty years of support, and with their encouragement, I feel that I could overcome all the challenges and difficulties in my life. This piece of research is a return of their love and faith in me.

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Abbreviations

AHP	Analytic Hierarchy Process
AIS	Automatic Identification System
ALARP	As Low As Reasonably Practicable
ARI	Average Risk Index
BN	Bayesian Network
BRB	Belief Rule Base
BR-BN	Belief Rule-based Bayesian Network
CI	Consequence Index
CLA	China Logistics Association
CLSCM	Centre for Logistics and Supply Chain Management
CPT	Conditional Probability Table
CREAM	Cognitive Reliability and Error Analysis Method
CSA	China Ship-owners’ Association
CSI	Container Security Initiative
CY	Container Yard
DAG	Directed Acyclic Graph
DoB	Degrees of Belief
DOSH	The Division of Occupational Safety and Health
D-S	Dempster-Shafer
EDI	Electronic Data Interchange
EPC	Electronic Product Code
ER	Evidential Reasoning
ETA	Event Tree Analysis
EU	European Union
FMEA	Failure Modes and Effects Analysis
FMECA	Failure Mode, Effects and Criticality Analysis
FRB	Fuzzy Rule Base

FTA	Fault Tree Analysis
GAL	Graph of All Linkages
GDL	Graph of Direct Linkages
HAZOP	Hazard and operability study
HMM	hidden Markov Model
ICI	Imperial Chemical Industries Ltd
IDS	Intelligent Decision System
IEC	International Electrotechnical Commission
IMO	International Maritime Organization
ISO	International Organization for Standardization
L/C	Letter of Credit
LI	Likelihood Index
LNG	Liquefied Natural Gas
LSCI	Liner Shipping Connectivity Index
MADM	Multiple Attribute Decision Making
MAIB	Marine Accident Investigation Branch
NGO	Non-Governmental Organisations
NIAC	National Infrastructure Advisory Council
PHA	Piminary Hazard Analysis
RFID	Radio Frequency Identification
RI	Risk Index
RIMER	Rule-Base Inference Methodology Using the Evidential Reasoning
RINA	The Royal Institution of Naval Architects
RPI	Risk Priority Index
RPN	Risk Priority Number
RM	Risk matrix
SD	Standard Deviation
TAPA	Transported Asset Protection Association
TEU	Twenty-foot Equivalent Units
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution

MCSC	Maritime Container Supply Chain
UNCTAD	United Nations Conference on Trade and Development
WMTN	Worldwide Marine Transportation Network
WSC	World Shipping Council

CHAPTER 1 - INTRODUCTION

Summary

This chapter provides a general analysis of the research background that helps to understand the research necessity from a practical viewpoint. The challenges of conducting the research are demonstrated following the explanation of the research objectives and statement of the hypothesis. The methodology employed in the research is also presented and justified. Finally, this chapter describes the layout and the scope of the thesis and summarises the deliverables and contributions to knowledge and achievements against research objectives.

1.1 Research Background

Container shipping in large part has promoted globalization and driven the rapid economic development over the past few decades. Container shipping has become increasingly important after its wide application from the 1970s owing to its significant advantages in promoting the standardization of cargo packaging and transportation, which enhances loading and unloading operation efficiency and dramatically reduces the costs of transport and the risks of cargo damage. It provides the foundation needed to achieve the intermodal transportation among the global logistics system. However, with globalization and outsourcing practices, there are more and more members involved in the container shipping process, which increases its complexity considering the requirements of commercial partners throughout the globe. Responding to this situation, container liner shipping has evolved from the original transport service of shipping lines to an advanced container supply chain system, which can be regarded as a specific type of supply chain with the rapid development of container transport and large-scale international trade (Hu, Yang and Huang, 2009). The integration of the supply chain in container shipping can be beneficial to all the members being involved in terms of their competitiveness (Lam and Van de Voorde, 2011). According to Meijer (2007), a container supply chain can be defined as:

"*The network of organizations that are involved, through upstream and downstream linkages, in the different container transport related processes and activities that produce value in the form of products and services in the hands of the ultimate consumer (shipper or consignee)*".

In this study, we mainly focus on the maritime segment of a container supply chain, involving container port/terminal operations and seaborne container transportation[1], which is referred to as a maritime container supply chain (MCSC). Developed from the traditional container shipping, an MCSC shares some characteristics of both container shipping and maritime supply chains such as high capital intensity, being easily impacted by fuel price and exchange rate, being limited by inflexible supply of container ships, facing the problem of empty container reposition, and having to follow international maritime regulations (Chang, 2013). These characteristics indicate that an MCSC is associated with a wide range of risk sources in a complex and volatile international environment, and the complicated physical structure of the global MCSC system makes it more likely to be exposed to many more possible undesirable hazards. As all parties involved in an MCSC (e.g. consignees, consignors, ports, terminal operators, and agencies) closely interact with each other, the overall performance of the MCSC will be deteriorated if any of its parts is negatively influenced by hazards and/or security threats. Therefore, it is important to develop suitable tools for effectively identifying the hazards, analysing their associated risks, and measure their impact on the system performance under the challenges of uncertainty and complexity across the global environment (Thun and Hoenig, 2011), in order to build a more efficient and resilient MCSC.

1.2 Research Objectives and Their Hypothesis

The primary aim of this study is to develop a novel and integrated framework for risk assessment of MCSCs considering both local risk conditions of MCSCs and their global impact on the entire container supply network, so as to achieve the comprehensive safety evaluation of each individual MCSC within the global container maritime logistics system. The newly developed models and methods will help to provide a clear insight into the risks existing in MCSCs and enhance their resilience under various circumstances. The results will offer a useful reference for stakeholders such as policy makers and MCSC operators, enabling them to improve their policy-making operations and risk management actions. In order to achieve this aim, some subsidiary objectives need to be carefully addressed. They are:

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[1] Although the landside logistics of containers is beyond the scope of this paper, the proposed framework for risk factors analysis has been applied to other container transport modes (e.g. road and rail) in the authors' on-going research project.

- To understand the technical challenges in hazard identification, risk assessment, and resilience applications in MCSCs through conducting a literature review.
- To develop a novel risk classification framework for identifying risk factors existing in MCSCs from different aspects and clarifying the relationships among the identified risk factors.
- To produce an advanced dynamic risk assessment technique using the fuzzy rule base and Bayesian network to realise the estimation of the identified risk factors.
- To develop a network-based model and analyse the importance of port and MCSCs within the global container shipping using the centrality measures.
- To integrate the estimations of local risk conditions of MCSCs and their global impact on the performance of the system into one framework using the evidential reasoning (ER) approach so as to achieve the comprehensive evaluation of MCSC resilience.
- To test the proposed models and methods by conducting sensitive analysis and case studies.

The hypothesis that the objectives depend on is that the most widely used uncertainty treatment theories such as fuzzy logic, Bayesian theory, Dempster-Shafer (D-S) theory and network analysis methods can be the foundation of and significantly contribute to developing novel and advanced risk management models in the context of MCSCs[2].

1.3 The Statement of the Problem

Complexity has been identified as one of the most distinctive characteristics of the modern MCSCs, attracting much attention from both academia and industry (Kriheli and Levner, 2018). The complex MCSCs are closely associated with not only the complexity of physical structure and operational processes of the global MCSC system but also that of their risks existing in almost every segment of an MCSC. The complexity of the risks can be observed in, at least, the following three aspects: different risk forms, numerous existing risk definitions, and the inherent uncertainty feature of risks.

Different risk forms are reflected in the usage of diverse categorising methods. Some research classified the risk types into two broad categories including operational and disruption risks, internal and external risks (Trkman and McCormack, 2009; Olson and Wu, 2010), and

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[2] A number of academic papers gave been submitted and published (see Appendix Eleven) to validate the reliability of the deliverables against the objectives.

macro and micro risks (Tang, 2006). While, some applied ternary classification methods, such as environmental, network-related, and organisational risks (Jüttner, Peck and Christopher, 2003), or material flow, financial flow and information flow risks (Tang and Musa, 2011). There are also many other ways of categorising risks. For example, the Centre for Logistics and Supply Chain Management (CLSCM) in Bedfordshire (UK) investigated the risks in supply chains considering five main risk sources, which are demand, supply, process, control, and environmental risks (CLSCM, 2003). Tang and Tomlin (2008) discussed risks originating from supply, process, demand, intellectual property, and behavioural and political aspects. However, categorising methods developed in previous work is too broad to provide specific information needed for the risk management of MCSCs. Besides, the majority of the studies were carried out to analyse several specific kinds of risks focusing on one or two or several risk types, which is fragmental. This calls for a holistic MCSC risk management framework to cover as many risk sources and factors as possible for analysing and managing multiple types of risks in MCSCs, in order to provide an inclusive risk picture in the container shipping industry.

As an interdisciplinary term, risk per se has not met an agreed definition, and different ways of understanding the risk concept can be observed in the literature in different research areas ranging from economy to psychology, and from business to engineering (Aven, 2012). It is still the case in the context of supply chain risk management. As indicated by the review of Heckmann, Comes and Nickel (2015), although only a few authors explicitly defined what supply chain risk is in their research, different definitions of supply chain risk exist simultaneously. Jüttner, Peck and Christopher (2003) defined risk as the effect of mismatch between supply and demand. Ellis, Henry and Shockley (2010) emphasised the potential loss associated with the disruption of supply. Differences between the existing supply chain risk definitions indicate a different understanding of risks, which results in a variety of ways approaching the risk analysis. For example, most of the researchers mainly focused on the two widely investigated aspects of risks - the occurrence likelihood and associated adverse outcome (e.g. Chen and Yano, 2010; Vilko and Hallikas, 2012; Chang, Xu and Song, 2014). While, some pointed out the importance of visibility (Caridi et al., 2014), as the lack of visibility of upstream and downstream flows and stocks makes it difficult to make optimal operational control measures at each stage of the MCSCs. Thus, it is important to select suitable and rational risk attributes/parameters and modelling techniques for the successful risk assessment of MCSCs considering both the accuracy of the results and the cost-effectiveness of conducting the risk assessment.

Uncertainty is also considered to be a major contributor to the complexity of the risks (Yang et al., 2005b), making it even more difficult to identify and assess the risks. Generally, the uncertainty is interrelated with risks, and it is almost inevitable in our daily life. Aven and Renn (2009) defined risk as a kind of uncertainty about the severity of the consequences. Bedford and Cooke (2001) argued that probability could be regarded as a measure of uncertainty about future events and consequences. The uncertainties associated with the MCSCs' risks have different sources and diverse forms. Three major types of uncertainties have been identified, which are fuzziness, incompleteness and randomness (Blockley et al., 1997). Fuzziness represents imprecision. It occurs during the subjective interpretation processes especially when human judgements are involved. For example, fuzziness will be produced in an expert survey when risk parameters are measured using linguistic terms (which are more suitable to represent human knowledge rather than precise values in such situations or in the case of a lack of statistics data). Incompleteness refers to the knowledge that we do not know and thus cannot be modelled. This is usually the reason for the deviation of results between a theoretical model and the reality. Incompleteness is a kind of epistemic uncertainty. It may occur due to the incomplete understanding or unavailable information of the MCSC systems being modelled. Randomness can be defined as the lack of a specific pattern in events. The randomness depends on the variations between observations and the number of observations, which is usually expressed in terms of sample variance. The complex dynamic behaviour of the MCSCs further increases the randomness of probability distributions of risk factors. The above-mentioned situation highlights the importance to understand and appropriately deal with the uncertainties in MCSCs by using advanced risk modelling and analysis methods.

In the previous studies, risk assessment of MCSCs is mainly conducted from a local perspective without the consideration of the impact of MCSC risk condition on the overall performance of the entire MCSC system. This may lead to a sub-optimal decision in terms of the allocation of limited resources on supply chain risk management from a system perspective because the MCSC with the most severe risk condition does not mean that it also has the most impact on the overall performance of the MCSC system. For example, the shutout of the Port of Shanghai (China) is believed to have much more influence on the global container shipping performance than that of the Port of Mogadishu (Somalia) due to the huge container throughputs, leading position, and excellent global connectivity of Port of Shanghai, although the risk condition of the latter is higher because of its relatively undeveloped infrastructure and frequent pirate attacks nearby. The breakthrough of the network research in recent years (e.g. Watts and Strogatz, 1998; Barrat et al., 2004; Opsahl, Agneessens and Skvoretz, 2010) has provided new opportunities to investigate the complexity of physical MCSC systems from a network perspective, which is believed to be able to offer more insight into the complexity of the container shipping network in terms of the spatial and topological structure. Some applications can be found, for example, in Ducruet and Notteboom (2012), Li, Xu and Shi (2015), Ducruet (2017), and Xing and Zhong (2018). However, a novel model is still needed to combine the structural importance and the risk status of MCSCs together in order to provide more comprehensive evaluation results of the system performance.

1.4 Research Methodology and Scopes of the Thesis

The methodological view on risk assessment adopted in the thesis is originated from two streams. On the one hand, a series of risk models are generated to support hazards identification, risk analysis and assessment of MCSCs under uncertainty, while on the other hand, a network-based approach is developed to measure the importance of MCSCs from a physical structure perspective. Finally, the two branches merge together by using an integrated framework for the evaluation of MCSC performance from a systematic view. Generally speaking, the methodology consists of six interrelated essential steps of realising the research objectives as follows:

1. Research background analysis and challenge identification.
2. A critical review of the MCSCs in terms of the operation process, development, and literature related to the challenges identified in Step 1.
3. The development of a novel framework for identifying risk factors of MCSCs in a hierarchical structure based on the review in Step 2, and classifying those risk factors using a risk matrix approach.
4. Fuzzy rule and BN based risk modelling for providing a more effective and powerful technique to deal with the uncertainties involved in the assessment of risk factors of MCSCs identified in Step 3.
5. Network-based analysis of the importance of MCSCs from a perspective of the container shipping network topological structure.

6. Development of an integrated approach for combining the risk assessment results in Step 4 and the structural importance of MCSCs obtained together in Step 5 so as to achieve the comprehensive evaluation of MCSC performance.

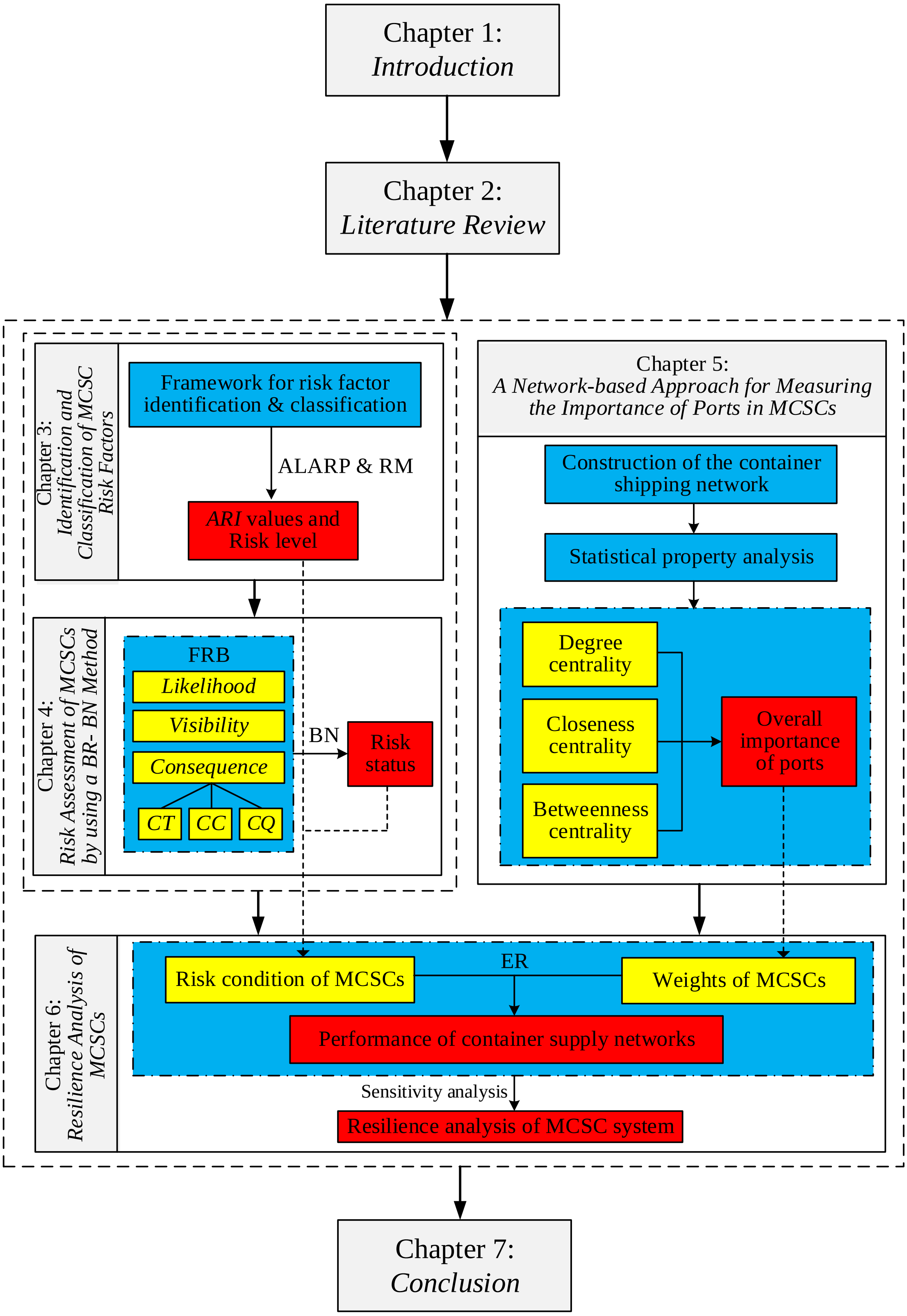


Figure 1.1. The structure of the thesis

A graphical flowchart is presented in Figure 1.1 for clarifying the logical backbone of the complex methodology. More detailed explanations of the relationship between the steps of the methodology are unified together with the study of the thesis layout and given in the following.

The research scopes are set up to surround the core of the thesis, which is risk management of MCSCs. The intention is to provide a hierarchical framework for risk identification, an advanced risk modelling method for risk assessment under uncertain environments, and an integrated approach for the evaluation of MCSC resilience considering both their local risk condition and global impact on the MCSC performance. The document therefore only explains the relevant theories and methods up to the level where they are used to suit the objectives and aims of the research instead of proving an in-depth analysis of the theories themselves. The proposed method considers the uncertain nature of the risks and the industry's requirements of instantly ranking the risk factors with updated information. It is particularly innovative when the importance of MCSCs is taken into consideration to support risk management in a complex global environment, compared to the traditional risk assessment mainly conducted from a local level which lacks the resilience impact analysis on the whole system.

The thesis is compiled in seven chapters. Following the discussion of the research process in ***Chapter 1***, ***Chapter 2*** reviews the important literature closely related to the current study. It includes the status quo of MCSCs, the demonstration of an MCSC's operation, the review of risk assessment methodologies and approaches related to MCSCs, and the attempt at broadly understanding the resilience concept and its applications in maritime transportation systems. The emphasis and kernel of the thesis start with ***Chapter 3*** and end with ***Chapter 6***. They are presented in detail as follows.

Risk factor identification is regarded as the very first step in risk management. ***Chapter 3*** proposes a structured framework composed of four levels of risk classification and identification. This chapter firstly identifies all the possible risk factors involved in MCSCs according to the reviewed relevant literature on risks in general container supply chains. After that, a Delphi expert survey is conducted to validate the risk factors and explore more risk factors that are not mentioned in previous studies in order to expand the coverage of the risk factor identification. The identified risk factors are preliminarily analysed in terms of their occurrence likelihood and consequence severity based on empirical data collected through a large-scale questionnaire survey (and an online survey). The risk matrix method and the ALARP principle are applied to further categorise the identified risk factors into different risk levels according to their *ARI* values so as to screen the most severe ones that need more attention.

However, the consideration of only two risk parameters (i.e. occurrence likelihood and consequence severity) may lead to the ignorance of some useful risk information in terms of the analysis of the identified risk factors in practice. Therefore, ***Chapter 4*** makes two main extensions based on the traditional risk definition to rationalise the risk assessment of MCSCs. Firstly, the visibility of risk in a supply chain is considered, which indicates the level of awareness of the risk factors to be estimated. Secondly, the consequence parameter is decomposed into three specific ones according to their risk impact on the performance of MCSCs. They are time delays, economic costs, and damage to quality. Having done that, a novel risk evaluation method is proposed by incorporating the fuzzy rule base (FRB) with Bayesian network (BN) techniques in a complementary way, where FRB is used to model the relationships between risk parameters and risk status of risk factors in a logical manner under uncertainty, and the BN modelling is used to achieve the risk inference and prioritise risk factors in a real-time way. The proposed method is believed to be able to provide sensitive and flexible risk results without sacrificing the easiness of the modelling process and transparency of risk information.

Chapter 5, as the other research branch in parallel with the risk factor assessment, aims to provide a theoretical basis for the importance measurement of MCSCs from a network perspective. In this chapter, the maritime container supply network is abstracted to a graph, in which container ports constitute the nodes and liner shipping services provide the links within the network. Based on that, the statistical properties of the sample container shipping network is investigated in terms of its degree, degree distribution, average path length, and clustering coefficient, in order to reveal the topological features (e.g. small-world phenomenon) of maritime container shipping network. Different centrality measures are applied to study the position of ports with respect to their connectivity, accessibility, and transitivity within the network, and a novel indicator is further proposed for comprehensively measuring the overall importance of ports taking into consideration the influence of both ports’ centralities including degree, closeness, and betweenness centrality and annual container throughput. As such, the proposed importance measure is able to reflect not only the topological features of ports but also their individual operational and development status.

Based on the research results from the previous chapters, ***Chapter 6*** develops an integrated approach to comprehensively evaluate the resilience of MCSCs considering both the local risk conditions of MCSCs and their global impacts on the performance of the whole supply network. The *ARI* values calculated by using the risk matrix are used to calculate the relative weights of risk factors, based on which, the estimations of each identified risk factor are synthesised using the ER approach to provide the risk conditions of MCSCs; the score of port importance is applied to support the measurement of MCSC importance within the targeted maritime container supply network; The ER approach is utilised again to combine the risk conditions and structural importance of MCSCs to achieve the overall performance evaluation systematically. The sensitivity analysis helps to quantify the impact of each individual MCSC on the performance of the entire system. Finally, an empirical case study focusing on the operational risks is conducted form a shipping company's perspective to demonstrate the feasibility and applicability of the proposed method.

Chapter 7, the conclusion chapter of this thesis, summarises the main research findings on the identification, classification, and assessment of risk factors associated with the MCSCs and highlights the novel and sound risk assessment methodology with many original and advanced risk modelling and analysis methods. The research findings have been disseminated through academic publications in research journals and at international conferences making contributions to academic and industrial areas for further research on risk management of MCSCs. The limitations of the current research are outlined, and the opportunities arising from the proposed methods are suggested for future improvements and applications.

Based on this research, the panorama picture of risk factors in MCSCs will provide a reference for exploiting research gaps of MCSC risk management in follow-up studies and provide useful insights for managers in better understanding the risks of their companies in daily operations from a whole supply chain perspective. The risk modelling and reference techniques can support the real-time risk assessment and decision making in the container shipping industry, and in-depth analysis results of the identified risk factors can be used to determine which parts deserve more attention in daily operations so as to rationalize the safety resource allocation of a company for accident prevention, and put forward suitable risk mitigation countermeasures as well. The vulnerability analysis of the container shipping network sheds light on the identification of important ports from a more comprehensive perspective considering both its topological structure and operational condition, which can be helpful for daily operations and management of container shipping routes. The integrated framework for evaluating the overall supply network performance can provide guidance for managers on the proper management of risk factors from a systematic viewpoint, which is also believed to be beneficial to the shipping industry. Thus, this research will contribute to the risk management of MCSCs from both academia and industrial aspects.

CHAPTER 2 - LITERATURE REVIEW

Summary

This chapter presents an overview of the container shipping industry in terms of its development situation, and the three main logistics flows associated with the operational processes of MCSCs. The fragments of isolated investigations on the identification, analysis, and assessment of risk factors in MCSCs are gathered to provide critical insights into the risk management of MCSCs. An emerging concept, which is, becoming popular rapidly in recent years - resilience - is also reviewed in a relatively broad range of research fields, in order to facilitate its further application in the risk management of MCSCs. The research gaps identified in this chapter indicate the significance and value of the work to be conducted in the following chapters.

2.1 Introduction

The expanding scale and increasing volume of international trade, development of transportation infrastructure, and technology innovation in the last several decades have contributed to the rapid and significant growth of container shipping worldwide. However, the growth in globalisation and complexity of international container transportation systems also brings uncertainties into MCSCs, thus making it difficult yet necessary to manage risks properly and efficiently. The statistics show that in the past decade, MCSC risks caused the loss of billions of dollars in the European Union (EU) alone and the number of accidents and severity of the consequences are growing fast because of the growth of container transportation. Taking security risk as an example only, we see the estimated losses of 8.2 billion Euros due to cargo crime across the whole of Europe according to the Transported Asset Protection Association (TAPA) in the 2007 EU Parliament report (TAPA, 2017). Cargo crime incidents doubled in EU in 2014-2016 with an annual increase rate of 115% (Lloyd’s list, 2017). In terms of container loss at sea, based on the results of the nine-year period (2008-2016) surveyed, the World Shipping Council (WSC) estimates that there were on average 568 containers lost at sea each year, not counting catastrophic events, and on average a total of 1,582 containers lost at sea each year including catastrophic events. On average, 64% of containers lost during the last decade were attributed to catastrophic events (WSC, 2017a). Accidents may occur during every stage of the MCSC processes, which hinders safe and efficient operations. The risks occurring in modern MCSCs come from not only the technical failures during container shipments, but also the vulnerabilities at wider levels such as political, managerial, and man-made threats. Both academics and industry have initiated research on more powerful and effective methods, and tools, to manage the MCSCs. Therefore, it is significant to give an overall and detailed review of the MCSC operational processes, risk factor identification and risk assessment research related to MCSCs under such an uncertain environment, and the emerging methods and models in today's supply chain risk management, in order to demonstrate the necessity and motivation of this research.

2.2 Overview of the Maritime Container Supply Chains

2.2.1 The Status Quo of the Container Shipping Industry

Maritime transportation is at the core of international trade due to its outstanding advantages compared to other transport modes, accounting for around 80% of the volume of goods transported around the globe, and this share is estimated to be even higher for most developing countries (WSC, 2017a). Containerized transport service, as an irreplaceable part of the global maritime transportation system, is responsible for the most trade in manufactured and intermediate goods. In terms of cargo value, containerized general cargos exceed 90% of all general cargos (UNCTAD, 2017). Thus, containerization links the producers with the ultimate consumers and facilitates the rapid development of the global economy. As shown in Figure 2.1, following the negative impact from the financial crisis in 2008, global containerized trade continued to expand after 2009, and reached an expansion rate of nearly 5 per cent in 2017, with volumes attaining an estimated 145 million 20-foot equivalent units (TEUs) (UNCTAD, 2017). The recovery trend from 2015 to 2017 was driven by volume growth in the peak leg of the Asia-Europe trade, intra-Asian cargo flows and positive trends in the trans-Pacific.

In terms of different cargo types in the seaborne trade, Figure 2.2 reveals that the volume of seaborne containerized trade has increased more than fifteen times during the last three decades, and its share of world seaborne trade shows an increasing trend, taking up 23.8 per cent of the total dry cargo volumes in 2016.

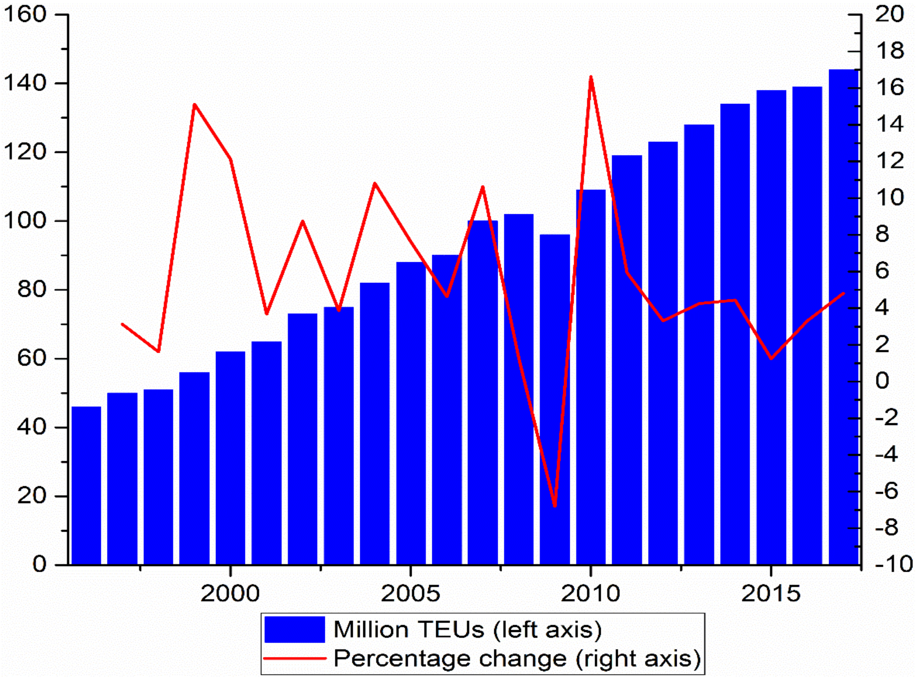


Figure 2.1. Global containerized trade in recent two decades (Millions TEUs and annual percentage change)
Sources: By author based on the data from the Review of Maritime Transport 2017

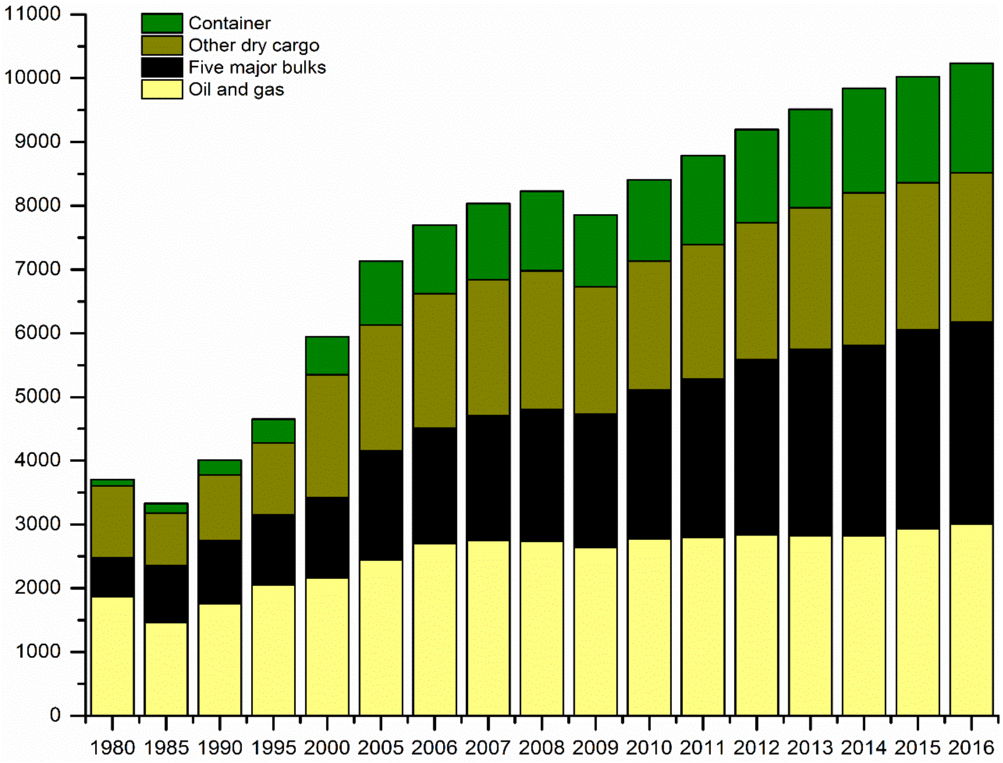


Figure 2.2. International seaborne trade from selected years (Millions of tons loaded)
Sources: By author based on the data from the Review of Maritime Transport 2017

A country's participation in global seaborne trade and the ability to provide reliable shipping services are important factors in determining nations' competitiveness of container transport (Panahi, Ghasemi and Golpira, 2017). In 2004, the United Nations Conference on Trade and Development (UNCTAD) developed a novel indicator to quantify a nation's containerized liner trade which is known as Liner Shipping Connectivity Index (LSCI). The LSCI is calculated based on the information of the world's container shipping fleet, consisting of five components. They are the number of ships deployed to and from each country's seaports, their combined container-carrying capacity, the number of companies that provide regular services, the number of liner services, and the maximum container ship size (UNCTAD, 2017). Accordingly, relevant information related to the top ten countries in terms of their annual capacity of total container ship deployment is collected and summarised in Table 2.1.

Table 2.1. Top ten countries in terms of total container ship deployment

Country	Deployed annual capacity (10^3 TEU)	Number of ships on services	Number of operators	Number of services	Maximum ship capacity (TEU)
China	85347.7	1996	907	463	18506
Korea	40924.8	1017	465	245	18506
Malaysia	36663.7	906	365	196	18506
US	36154.5	990	437	200	13950
Germany	26427.5	621	253	143	18350
UK	24946.1	594	235	139	18506
Spain	21685.9	605	213	151	18506
UAE	20468.7	393	158	94	17387
France	18823.5	466	176	87	17387
Japan	18584.6	594	291	204	12939

Sources: Collected from Review of maritime transport 2017 (until May 2017).

2.2.2 The Characteristics and Operations of MCSCs

Normally, traditional supply chains can be understood as an integration of all activities associated with the flow and transformation of goods from raw materials to end users encompassing processes such as sourcing, production, and inventory management. However, MCSCs are developed on the basis of both the widespread application of containers in the global logistics system and the urgent requirement of safe and resilient container shipping services in the increasingly complex and uncertain environment. It is a kind of transport-oriented service. From a function perspective, an MCSC can be regarded as an organic integration of the container transport and transhipment services, by means of different transport modes (e.g. rail, road, air, and maritime) from the origin to the destination, under the cooperation of different service providers involved in it, in order to realise the efficient and accurate shipment of cargos according to consignors' requirements. The stability of MCSCs is relatively low compared with that of a traditional supply chain, due to the heterogeneity and volatility of customer needs. The unique characteristics of MCSCs are as follows (Li, 2016):

- Fast and low cost. This is mainly due to the standardisation which can be regarded as the most prominent feature of MCSCs. During the logistics process, containers rather than cargos are taken as the basic units which can be handled anywhere in the world (ISO standard) through specialized modes (e.g. ships, trucks, wagons, and trains), handling infrastructures and equipment, so that the operational efficiency of container loading, unloading, and handling at transhipment centres and container terminals can be improved. The usage of containers also reduces the packing expenses, the warehousing costs, and the costs due to loss or damage as well since the containers are easier to pack and store and can protect contents on long journeys. Thus, the level of standardisation (as well as collaboration among different service providers) will influence the efficiency of the entire MCSC.
- A wide range of usages. Container units may vary in dimension, structure, materials, and construction. Various types of shipping containers including open top containers, refrigerated containers, thermal containers, and special purpose containers, are being used in order to meet requirements of all kinds of cargos of different sizes. Thus, MCSCs have a wide application in global freight transportation.
- Complex operational process. A typical door-to-door journey using container supply chains involves the interaction of approximately 25 different participants, generates more than 30 documents, and needs to be handled at as many as 12 to 15 physical locations (Yang et al., 2005a). Due to the geographic dispersion of the supply chain members, multiple transportation modes are usually involved in MCSCs to support the transport of containers worldwide. However, the laws, regulations, procedures and documents concerning container transportation are not uniform in different countries, making the situation of international multimodal transport even more difficult.
- Repositioning of empty containers. The repositioning of empty containers is one of the most complex problems concerning global cargo distribution. It is estimated that empty containers account for about 10% of existing container assets and 20.5% of global port handling (Rodrigue, 2017). Trade imbalance has been identified as one of the major causes of the empty containers repositioning problem, because a region that imports more than it exports will face the accumulation of empty containers, while a region that

exports more than it imports will face a shortage of containers. Container repositioning can occur at local, regional, or international scales, depending on the nature of the container flow imbalances.

- A high level of uncertainty. Uncertainties in MCSCs come from different sources. Firstly, differences exist among various transport modes in terms of their layouts, transport technology and equipment, infrastructure, and shipping capacity; secondly, the uncertainties in the external environment such as the change of macroeconomic situation, international trade development, market demand, and national and customs policies will also influence the turnaround time and costs of MCSCs; thirdly, as all the enterprises involved in MCSCs such as shipping companies, shipping agents, container terminal operators, and port enterprise, have their specific development situation and goals, they are among the competition and cooperation relationships with each other, making the situation more complex.

Although this research mainly focuses on the maritime segment, the whole operational process is introduced in this subsection in order to maintain the integrity of a general container supply chain. A typical operational process of the container supply chain (including the movement of containers) is developed and designed by the author based on the work of Van Oosterhout (2003), Lu and Wang (2008), and Chang (2013), as illustrated in Figure 2.3.

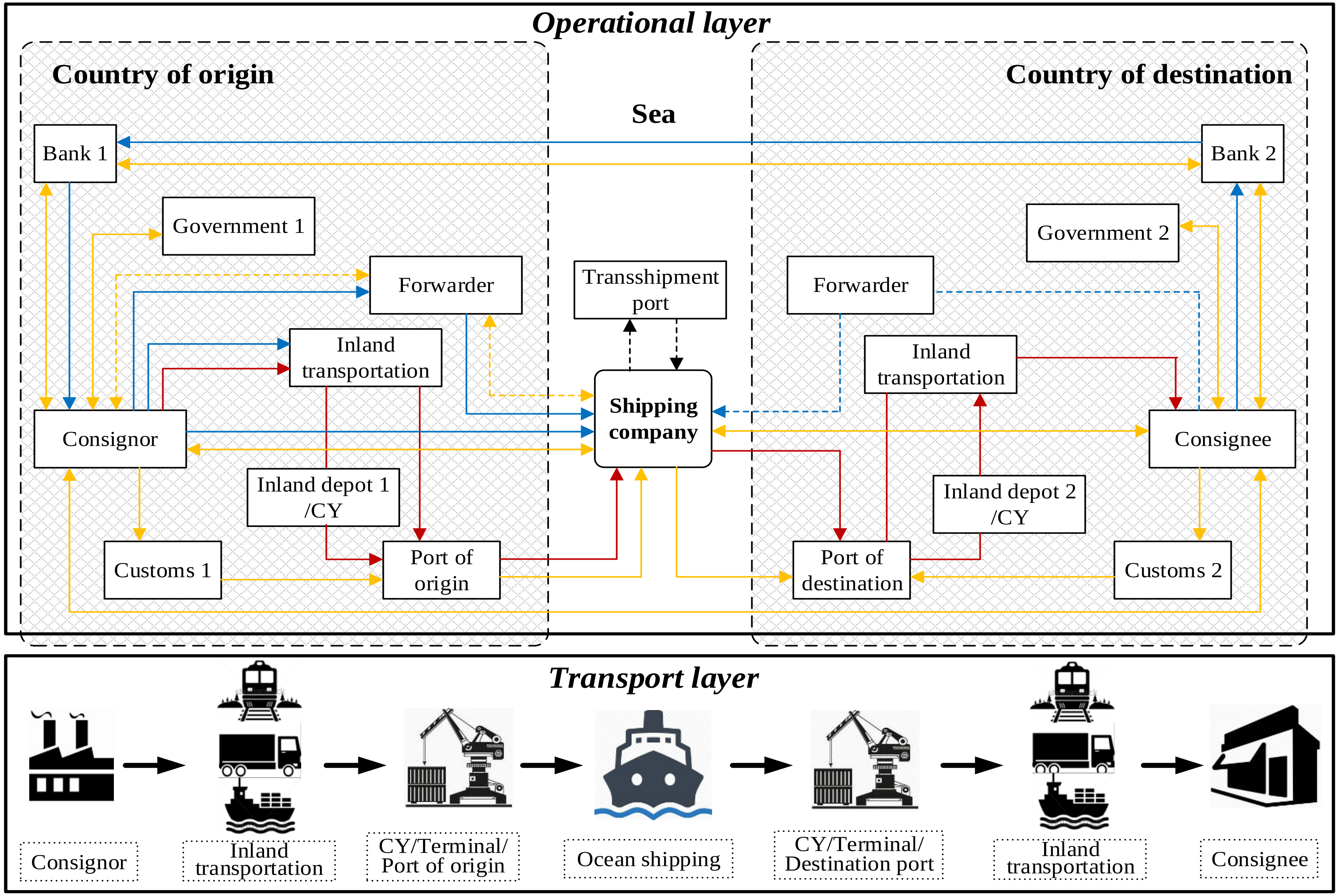


Figure 2.3. Flow chart of container supply chain service

Source: author

There are three significant flows in a container supply chain, which are physical flow, information flow, and financial/payment flow (Chang, Xu, and Song, 2015). Figure 2.3 demonstrates the operational process among the supply chain actors, where the physical flow is represented by red arrows, the information flow by yellow arrows, and the financial/payment flow by blue arrows.

1) Physical flow

Physical flows involve the movement, transhipment, and storage of goods. They are the most visible piece of a supply chain. In a container supply chain, it refers to the movement of container cargos. The consignor transports goods to the inland deport or the container yard through inland carriers. Following that, the goods are transferred to the port of origin to wait for loading. After being placed on board, the container can be moved and transhipped through other ports onto other vessels by shipping companies before arriving at its destination port for unloading. Finally, the goods are transported to the consignee by inland carriers in the country of destination.

2) Information flow

Information flows allow the various supply chain partners to coordinate their long-term plans, and to control the daily flow of goods along the container supply chain. The information includes the data or documents that need to be transferred for cargo processes. As indicated by Figure 2.3, the information flow between the consignee and the consignor indicates the negotiation of the cargo price between them. Besides, both the consignor and consignee have to apply for the export and import documents respectively from their own governments and get permission before transporting the cargos. At the same time, the consignee needs to apply for a letter of credit (L/C) from the paying bank (Bank 2), and the paying bank will transfer the L/C to the consignor through the Advising Bank (Bank 1). The consignor can directly ask the freight price and book container space from the shipping company, or through the forwarder. In the next step, the consignor needs to declare export to the customs, and the customs will check and discharge the cargos in the container yard (CY). After that, the shipping company will contact the CY to load the cargos. The shipping company will also inform the consignee after the arrival of the cargos. The consignee needs to declare import to the customs before taking the cargos.

3) Financial flow

Financial flows refer to monetary payment from the customer sector to the business sector that provides goods or services (Chang, 2013). According to Coyle, Bardi, and Langley (2003), the payment flow traditionally has been deemed as one-directional in a supply chain. As shown in Figure 2.3, the financial flow between the consignee and the consignor is composed of two parts. For the first part, after the contract being signed by the consignor and the consignee, the Bank 2 will check the credit of the consignee and transfer the money to the Bank 1. Then Bank 1 will pay the money for goods to the consignor. For the other part, the consignor will pay the money to the shipping company to book the cargo space whether through the forwarder or not. The consignor also needs to pay for inland transportation in order to transport the cargos to the port of origin. After the cargo arrives at the port of destination, the consignee needs to pay the money to the inland transportation on that side for collecting the cargos.

2.3 Risks and risk assessment of Maritime Container Supply Chains

In the risk management process, to clearly define the risk of MCSCs and fully investigate the connotation and attributes of MCSC risks will aid effective risk analysis.

2.3.1 Risk Concept in Maritime Container Supply Chains

2.3.1.1 Definition of MCSC Risks

Although the research on supply chain risk management showed an increasing trend in the last decade (as shown in Figure 2.4), only a few authors explicitly answered the question of what a supply chain risk is, and what characteristics it has. Yu and Goh (2014) regarded supply chain risks as the probability of occurrence of an adverse event during a certain period within a supply chain and the associated consequences which affect supply chain performance. Kull and Closs (2008) carried out the risk assessment in a simulation environment to examine supply risk issues within the context of a second-tier supply failure. In their study, the grounded definition of supply risks based on Zsidisin (2003) was "*the potential occurrence of an incident associated with the inbound supply from individual supplier failures or the supply market in which its outcomes would result in the inability of the purchasing firm to meet demand or threaten customer well-being and safety*". Other research on supply chain risk management using similar definitions included Goh et al. (2007), and Kähkönen et al. (2016). To minimise the supply chain cost with embedded risks, Kumar et al. (2010) defined supply chain risk as the potential deviations from the initial objective, which would result in the decrease of value at different levels. Overall, among the research with an explicit definition of supply chain risk, analysis on supply chain risk was generally approached from three aspects (Heckmann et al., 2015), including a) the probability of occurrence of triggering events and their adverse outcomes (e.g. Chen and Yano (2010); Yu and Goh (2014)), b) a deviation from the expected objective or value (which was often profit-, or cost-oriented) (e.g. Bogataj and Bogataj (2007); Kumar et al. (2010)), and c) the supply risk defined by Zsidisin (2003), which arose from individual supplier failures or market factors. However, most conceptual work with no explicit definition implies the risk to be a triggering event or a probability. An in-depth discussion on the definition of supply chain risks refers to Heckmann et al. (2015).

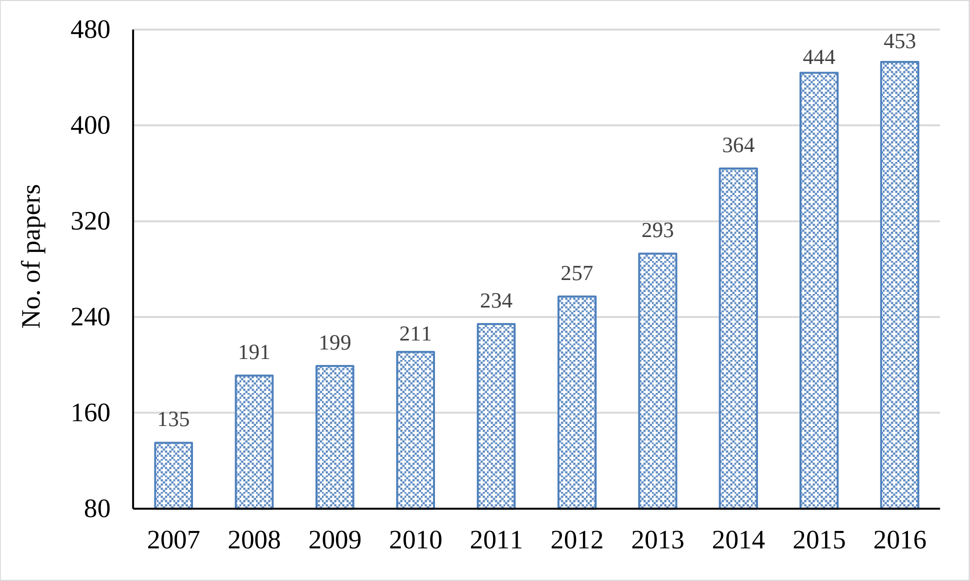


Figure 2.4. Distribution of papers by year of publication
Source: author

In this study, MCSC risks refer to the combination of the occurrence of a triggering event (or a certain situation) during the maritime transport of containers and the associated outcomes which have the potential to negatively influence any component/process of an MCSC, such as damaging port infrastructure, container ships, cargos, and/or environment, causing injury/death of seafarers, interrupting container shipping business, and damaging reputation of shipping companies and maritime authorities.

2.3.1.2 Risk Parameters

Although there are differences between widely applied risk assessment methods, common elements have been observed in most of the conceptualisation of risks (Manuj and Mentzer, 2008), which are:

- The risk factors/hazards

- The occurrence of the risk factors, i.e., the probability/likelihood of the occurrence of a specific risk factor
- The consequence that a risk factor may bring, i.e., the severity of adverse effects on the occurrence of a specific risk factor

For a risk to be measured, it is generally represented as *Risk* = (*P*, *C*), where *P* is the probability of a risk occurrence and *C* is the significance of the consequence. This is one of the most commonly used definitions in maritime supply chain risk analysis (Waters, 2007; Vilko and Hallikas, 2012; Chang, Xu and Song, 2014). It presents a simple and effective way to analyse risk, which has been used together with other assessment methods such as loss exposure matrices (Yang, 2011), and risk maps (Chang, Xu and Song, 2014). However, the risk is a complex and interdisciplinary concept with a variety of parameters being involved in addition to the probability and consequence, such as uncertainty, exposure, and scenarios (Aven, 2012). For example, Aven (2010) defined it as *Risk = (P, C, U),* where *U* represents the uncertainty about *P* and *C*. He also tried to connect another parameter – the background knowledge (*K*) – to the subjective probability in the risk description, resulting in *Risk = (P, C, U, K).* Another example of the different elements of risk is seen in FMEA, where risk analysis takes into account three risk parameters: the probability of the failure, the severity of the consequence, and the chance of the failure being undetected (Yang, Bonsall and Wang, 2008). The chance of the failure being undetected is similar to risk exposure; this variable partly influences the likelihood that a hazardous event will occur (Manuj and Mentzer, 2008).

1) Likelihood

Likelihood refers to how likely a risk factor could negatively affect an MCSC. It is represented by the frequency of a risk occurring at a certain time period or the probability of it occurring, according to the certain circumstance investigated. It is a basic risk parameter that has been widely discussed and studied by a number of researchers, see, for example, Manuj and Mentzer (2008), Vilko and Hallikas (2012), and Chang, Xu and Song (2014), to name but a few.

2) Consequence

In the domain of maritime engineering, a hazard is normally defined as "*a physical situation or a condition with a potential for human injury, damage to property, or damage to the environment*" (DOSH, 2008). This definition indicates that the risk consequence varies. Some consequences are more tangible and easy to measure, such as time delay and financial loss.

Other consequences may be intangible and difficult to quantify and evaluate, such as environmental damage and reputation loss. According to Rausand (2013), the dimensions of risk consequences include:

- Impact on individuals, such as fatality and personal injury (including either physical harm or psychological trauma);
- Impact on the property, such as property loss and damage (e.g., loss of cargo, damage to containerships and port facilities.);
- Impact on the environment, such as soil, water, and air pollution, the greenhouse effect, and global climate change;
- Impact on business, such as business interruption and damage to a corporate image or reputation loss.

2.3.2 Risk Assessment Techniques

There are various methods being developed and applied to risk assessment in the industry in order to provide a reference for decision analysis. Those popular and most employed risk assessment techniques, as well as their features and applications, are introduced in the following subsections.

2.3.2.1 Traditional Risk Assessment Methods

Significant progress in the development and application of risk assessment methods in different industrial fields can be traced back to as early as the 1960s. The nuclear and petrochemical industries are the pioneers adopting various risk assessment methods to the system design, daily operation, and other aspects. The application of risk assessment in the shipping industry is relatively late. With the increasing importance of the shipping industry, various traditional risk assessment methods have also been used in the safety analysis since the mid-1990s, such as HAZard and OPerability studies (HAZOP) (Bendixen and O'Neill, 1984), Fault Tree Analysis (FTA) (Ang and Tang, 1984), Risk Matrix Method (Leung and Tummala, 1996), Event Tree Analysis (ETA) (Kumamoto and Henley, 1999), Preliminary Hazard Analysis (PHA) (Kumamoto and Henley, 1999), and Failure Mode, Effects and Criticality Analysis (FMECA) (Andrews and Moss, 2002).

1) Preliminary hazard analysis (PHA)

PHA is a method for qualitatively analysing hazards of a system and their risk levels. It is mainly performed at the preliminary design stage to identify hazards, associated causal factors, effects, risk levels, and mitigation measures in the case of insufficiently detailed design information. The level of risk is generally divided into four categories according to the frequency of the accident and its associated consequence severity, which are negligible, marginal, critical, and catastrophic. The analysis results are provided by the preliminary hazard list (Pillay and Wang, 2003a). A PHA process is described as follows (Kumamoto and Henley, 1999):

a) Define the system of interest;
b) Identify hazards;
c) Analyse the frequency and consequence severity of the hazards;
d) Identify the major hazards accruing to risk levels;
e) Use the analysis results in risk prevention.

The PHA is applicable to the analysis of all types of systems, facilities, operations, and functions, but focuses predominantly on identifying and classifying hazards early in the development of a system rather than evaluating them in detail. Mader et al. (2011) applied PHA in the development process of automotive embedded systems for the identification of hazards and top level safety requirements. A PHA was performed by Weibel and Hansman (2004) for two critical hazards (i.e. ground impact and mid-air collisions) of unmanned aerial vehicles in the national airspace system of America. However, it is worth noting that the results of PHA rely heavily on the subjective cognition and experience of the analysts. Another limitation is that the effects of interactions between hazards are not easily recognized.

2) Hazard and operability studies (HAZOP)

HAZOP was developed by the Imperial Chemical Industries Ltd (ICI) in 1974 to detail the safety analysis of complex technical equipment systematically. It is a structured technique for system examination based on the assumption that risk events are caused by deviations from design or operating intentions, in which deviations are identified by using a set of standardised guide words. Some common HAZOP guide words include “None”, “More”, “Less”, “As Well As”, “Part Of”, “Other Than” and so on. HAZOP is best suited for assessing hazards in facilities, equipment, and processes and is capable of assessing systems from multiple perspectives including design, environment, and operations. According to the latest international standard for HAZOP application guidelines published by the International Electrotechnical Commission (IEC), the procedure of HAZOP involves the following basic steps (IEC, 2016):

a) Define the scope and objectives;
b) Select the suitable analysis team;
c) Gather the information necessary to conduct a detailed study;
d) Subdivide the system into logical and manageable parts for efficient study;

e) Identify deviation by using guide words on each element;
f) Analyse the causes of deviations and their consequences;
g) Formulate appropriate countermeasures;
h) Record the examination and document the review proceedings.

As a qualitative assessment method for risk prevention at the design stage, HAZOP is simple and easy to perform. At the same time, analysis results generated from HAZOP can be used as the basis for further quantitative analysis by other risk assessment methods (e.g. FTA). For example, Li et al. (2015) for the first time applied the HAZOP to identify the operational hazards of the Chinese train control system. However, many reasons exist that may lead to the failure of HAZOP in practice. Some prevalent ones include a lack of experience, failure to communicate, management shortcomings, and poor loss-prevention practices (Mckelvey, 1988).

3) Failure mode, effects and criticality analysis (FMECA)

FMECA began with the standard developed by the US Military, MIL-STD-1629. FMECA is an extension of the Failure modes and effects analysis (FMEA) by including criticality analysis. As an inductive and proactive analytical method, FMECA studies the effects of single component failures on the system, and through the control of high-risk failure modes, the overall safety of the system is achieved. It is useful for exhaustively listing of all potential initiating faults. The FMECA procedure typically consists of the following step:

a) Define the system and create a block diagram of it;
b) List items or functions of the system in the worksheet;
c) Identify potential failure modes;
d) Analyse failure effects and causes;
e) Perform criticality computations and determine critical items;
f) Produce a list of recommended actions

Sayareh and Ahouei (2013) applied FMECA to the cargo handling operations of marine bulk terminals in order to reduce the delay risk. Based on the idea of FMECA, Yang and Wang (2015) proposed a novel framework for analysing engineering system risks by incorporating the fuzzy rule base and evidential reasoning. However, it is noted that the Risk Priority Numbers (RPNs) employed by traditional FMECA for ranking risk factors suffers from some weaknesses. One of the critically debated limitations is that equal RPN values may generate different risk implications (Mandal and Maiti, 2014). Besides, the relative importance among the three risk parameters is ignored when calculating the RPNs.

4) Fault tree analysis (FTA)

FTA was originally developed in 1962 at Bell Laboratories, under a U.S. Air Force study for the evaluation and estimation of system reliability and safety. FTA is a top-down process of deductive reasoning, which is widely used to estimate the probability of an undesired event resulting from a sequence of failure events in a diagrammatic manner. As one of the most widely used methods in the safety engineering, it can handle both quantitative and qualitative assessments. Generally, the following steps are needed to conduct an FTA (Lee et al., 2009):

a) Define the system and collect accident data for the target system;
b) Identify representative failures to be studied as the top events;
c) Construct the fault tree by performing a step-by-step analysis in a top-down process;
d) Simplify the fault tree and conduct the qualitative evaluation;
e) Quantify the probabilities of failures and identify the high-risk sources;
f) Propose countermeasures according to the results.

FTA is clear in logic and easy to present the abstraction of the target systems for risk inference. Thus, its application can be widely seen in the analysis of system safety and reliability. Chen et al. (2009) developed an FTA-based approach to investigate the risk factors of supply chain disruption, and diagnose the supply chain reliability. Gong, Chen and Gui (2012) constructed the fault tree of the automobile logistics service supply chain system failure and introduced triangular fuzzy numbers for describing the probability of the basic events. However, the main difficulties of achieving FTA lie in how to establish a scientific and reasonable fault tree model, which requires the rich knowledge and experience of analysts.

5) Event tree analysis (ETA)

ETA is a bottom-up inductive inference method used to evaluate the process and its events leading to a possible accident. It is based on binary logic, that is, an event can either happen or not. Then, each alternative is considered as a new initial event, and the analysis continues until the final result is found. With this forward process, the sequences of events in the process leading to the accident will be shown in a graphical logical model. This technique can be applied to a system early in the design stage to identify potential risks and prevent negative outcomes of the risks from occurring. Typical steps of conducting ETA include (Ericson, 2005):

a) Define the system and set accident scenarios;
b) Identify the initiating events;
c) Develop the event tree model;
d) Quantify the probability of the event paths and evaluate their risk;

e) Take corresponding measures to reduce the risk of the path that is not acceptable.

ETA is able to clearly present the dynamic development process of accidents in order to support analysts on revealing and analysing the accident paths. Based on the probability of occurrence of events in each stage, the key path with the highest risk can be identified so that the corrective actions can be taken to prevent the accidents from happening. In the work of Fu et al. (2016), ETA is used to model the different consequence scenarios of liquefied natural gas (LNG) leakage on board LNG-fuelled ships. According to the ETA model of LNG leakage, three final scenarios of LNG leakage are identified, which are flash fire, vapour cloud explosion, and pool fire or jet fire. Chu and Wang (2012) combined Markov chains with ETA to deal with the uncertainties of some stochastic variables of the probable fire scenarios. One major limitation faced by ETA is that many initial events may exist when dealing with complex systems, which will result in a large event tree that is too complicated to evaluate, weakening its operability in reality. Moreover, similar to FTA, ETA also lacks the ability to handle partial dependence between components.

6) Risk matrix method

The risk matrix is also known as the Probability-Impact Matrix. The bases for risk matrix are the definition of risk as a combination of the frequency and severity of the consequences when it occurs (Markowski and Mannan, 2008). It is used as an effective screening tool during the risk assessment to categorise risks according to their importance, so that relatively important risks can be highlighted and forwarded for further analysis while trivial ones can be disregarded (Wang and Foinikis, 2001). The two-dimensional graphic representation of the risk matrix increases the visibility of risks and thus can assist management decision making. Generally, the following steps are required to build a risk matrix (Markowski and Mannan, 2008):

a) Categorisation and scaling of the frequency and severity of consequences;
b) Categorisation and scaling of output index (e.g. risk ranking number);
c) Develop risk-based rules;
d) Create a graphical edition of the risk matrix.

Due to its good applicability in risk assessment, the risk matrix approach has been recommended in national and international standards and spread through many application in the maritime industry. Yang (2011) employed the loss exposure matrix to identify the severity and frequency of risk factors originating from the container security initiative (CSI) on the maritime supply chain in Taiwan. Nwaoha et al. (2013) applied the risk matrix approach to identify the major hazards related to the LNG carrier operations. Zhang et al. (2013) used the risk matrix to assist in developing the inland waterway navigational risk model. In recent research, the risk matrix was used in the risk analysis to calculate the frequencies and consequence of identified hazards in order to achieve the formal maritime risk assessment of the Strait of Gibraltar (Endrina, Rasero and Konovessis, 2018). Furthermore, different mathematical approaches are also incorporated into the risk matrix to enhance its applicability, includi furtherng fuzzy logic and Borda method. A detailed introduction of some fundamental extensions on the risk matrix approach can be found in Ni, Chen and Chen (2010).

2.3.2.2 Risk Assessment under Uncertain Environment

With the further development of the probability theory in risk assessment, some inherent deficiencies of applying traditional risk assessment techniques are observed, and many risk assessment applications in the management-based field indicated that they are more possibilistic than probabilistic, and more qualitative than quantitative. Besides, the increasing complexity of modern multimodal logistic systems further brings in the uncertainties faced by risk assessment. Having emerged in the 1970s, possibility theory developed quickly and became one of the most popular approaches to reasoning under uncertain environment. This facilitates the development of some advanced risk assessment theories and methods such as fuzzy logic (Zadeh, 1965), Bayesian networks (BN), and evidence theory, showing some superiorities (e.g. better adaptability and rationality) when dealing with uncertainties. The incorporation of these methods into traditional risk assessment techniques also provides a way to deal with their limitations.

1) Fuzzy logic

As an extension of traditional/binary logic, the fuzzy logic introduced by Zadeh (1965) is built around the central concepts of a fuzzy set (which is a generalisation of the classical set theory). It is the logic that deals with situations, where it is difficult or sometimes impossible for an expert to provide clear true/false answers, by introducing the notion of the degree in the verification of a condition (Mendel, 2001). Fuzzy logic enables the combination of linguistic knowledge and numerical data in a systematic way, thus making it possible to process imprecise information and take into account uncertainties as well (Adriaenssens et al., 2004). Fuzzy logic-based methods are a powerful tool for modelling the behaviour of systems which are too complex or too ill-defined to allow for conventional quantitative techniques, or when the available information from the systems is qualitative and imprecise (Nait-Said, Zidani and

Ouzraoui, 2009). However, no perfect application of fuzzy logic in practice has been found until its combination with a rule base in the control of a non-linear dynamical system (Mamdani and Assilian, 1975), in which its importance as a powerful design methodology was highlighted and demonstrated.

A fuzzy rule-based system is perhaps the most common way to represent human knowledge and to model human reasoning in a systematic manner, because in this kind of system human empirical and heuristic knowledge is represented in an approximate and linguistic manner - IF-THEN rules - our own language of communication (Ross, 2009). This makes fuzzy rule-based systems an invaluable tool for expression when applied in engineering systems together with other mathematical models and data processing approaches in reliability analysis and safety assessment (e.g., Bowles and Peláez, 1995; Pillay and Wang, 2003b; Guimarães and Lapa, 2007; Kong et al., 2012; Polat, Aksoy and Unlu, 2015; Zhang et al., 2016; Wu et al., 2017). Some of the advantages of a fuzzy rule-based system include the ability to capture and preserve irreplaceable human experience, to develop a system more consistent than human experts, and to develop solutions faster than human experts can do (Abraham, 2005).

2) Bayesian networks (BNs)

The BN (also known as belief networks) method was developed based on the well-defined Bayesian probability theory and networking technique. A BN is a graphical presentation of probability combined with a mathematical inference calculation, which provides a strong framework for representing knowledge. It also has a good ability in modelling randomness and capturing non-linear causal relationships, so that the inference based on incomplete, imprecise and uncertain information can be achieved. Generally, a BN can be characterised as a directed acyclic graph (DAG) and an associated set of probability tables (Pearl, 1986). A DAG is composed of two parts: the set of nodes and the set of directed edges, where the nodes represent random variables and are labelled by the variable names, while the edges between pairs of nodes represent direct dependencies among variables that are connected. In particular, an edge from one node to another represents a statistical dependence between the corresponding variables, and a conditional probability table (CPT) associated with each node indicates how strong such causal dependence is. As a method that is both mathematically rigorous and intuitively understandable (Ben-Gal, 2007), the BN approach has been applied in a range of real applications, especially when predicting and diagnosing properties of a complex system are involved. However, one common criticism of the Bayesian approach exists in its requirement of too much information during the construction of CPTs. Thus, early work has been done, and it revealed that a combination of Bayesian approach and fuzzy logic could be beneficial to both by compensating their individual disadvantages (Bott and Eisenhawer, 2002).

3) Evidence theory

The evidence theory was first developed by Dempster (1967) and further extended by Shafer (1976). Thus it is also called the Dempster-Shafer theory of evidence (which is often shortened to D-S theory). The core of the D-S theory is the rule of the combination by which the evidence from different sources is aggregated. Assuming that the information sources are independent, the multiple belief structures can then be combined using the orthogonal sum (Wang and Yang, 2006):

$$m = m_1 \oplus m_2 \oplus \cdots \oplus m_k \qquad \text{Eq. 2.1}$$

where $\oplus$ represents the operator of the combination. Suppose subsets B and C defined on a common space θ are associated with belief structures m_1 and m_2 respectively. The combination of m_1 and m_2 can be achieved as follows (Alyami et al., 2016).

$$\left[m_1 \oplus m_2\right](A) = \begin{cases} 0, & C = \varnothing \\ \dfrac{\sum_{B \cap C = A} m_1(B) \times m_2(C)}{1 - \sum_{B \cap C = \varnothing} m_1(B) \times m_2(C)}, & C \neq \varnothing \end{cases} \qquad \text{Eq. 2.2}$$

where, $\left[m_1 \oplus m_2\right](A)$ is a basic probability assignment. $\sum_{B \cap C = \varnothing} m_1(B) \times m_2(C)$ represents the degree of conflict between the pieces of evidence. It is noted that the rule of combination is proved to be both commutative and associative (Shafer, 1976), which means that in the case of multiple belief structures, the combination can be conducted in a pairwise way. However, one major limitation of the original application of combination rule in the D-S theory is that irrational results will be concluded when aggregating multiple pieces of evidence in conflict (Murphy, 2000). The efforts spared on solving this problem promoted the birth and development of the ER approach partly (see Chapter 6).

4) Network-based analysis

The concept of centrality was first developed in the social network analysis (Newman, 2010), and different indicators of centrality have been designed to identify the most important node within a graph. Due to various meanings of importance and implicit assumptions about the way that flows move in a network, these centrality measures/indices can be generally classified into three categories (Wang and Cullinane, 2016): The most intuitive one is the degree-based centrality, which measures the importance of a node according to the number of direct connections associated with it. The second category is related to a node's ability to control the communication within the network. The two representatives under this category are closeness-based centrality and betweenness-based centrality. The former defines the most central node as the one moving through the entire network in the minimum time, while the latter considers a node as a central one if it is located on the path connecting pairs of other nodes. The last category defines centrality by considering influence measures (e.g. eigenvector centrality). Centrality measures provide an approach for assessing the vulnerability of the targeted system from a network perspective, which enables the collection of more useful insights on the supply chain risk management.

Centrality measures have been well applied in the global maritime transportation system, especially in the container shipping industry. These centrality measures are selected with respect to different characteristics of traffic flows and research purposes. Ducruet and Notteboom (2012) studied the spatial structure of the maritime network of container shipping, in which the degree centrality was applied as a local level measure of a port's connectivity and betweenness centrality as a global level measure indicating a port's accessibility. Ducruet (2017) investigated the multiplex properties of global maritime flows from various perspectives such as centrality, assortativity, traffic distributions, and correlations between links and nodes.

2.4 Resilience of Maritime Container Supply Chains

Transportation, as the core part of a container supply chain, provides the foundation for the movement of product from one location to another. It also supports the successful function of other flows involved in a supply chain. Therefore, its safety has been one of the issues with great importance in both industry and research. However, in recent years, the foci of transportation safety have been expanded from traditional risks through security, to resilience, and various studies have been conducted on transportation resilience from different perspectives. In view of this, this subsection presents a systematic review on transportation resilience with emphases on its definitions, characteristics, and research methods applied in different transportation systems/contexts, in order to offer new insights into the risk assessment of MCSCs.

2.4.1 Definition of Resilience

Currently, there are a number of different opinions and definitions of resilience in various application domains. For example, the National Infrastructure Advisory Council (NIAC) (2009) defined the resilience of an infrastructure system as its ability to predict, absorb, adapt, and/or quickly recover from a disruptive event such as natural disasters. In an engineering context, Hollnagel et al. (2007) defined resilience as the inherent ability of a system to alter its functionality in the face of unexpected changes (Hosseini et al., 2016), to name just a few. The definitions applied by previous studies associated with maritime transportation or general transportation systems are listed in Table 2.2.

Table 2.2. Existing definitions of resilience in the transportation field

Reference	Definition of resilience	Research topic
Haimes (2009)	The ability of the system to withstand a major disruption within acceptable degradation parameters and to recover within an acceptable time and composite costs and risks.	Transportation systems
Mansouri et al. (2010)	The function of the system's vulnerability against potential disruption, and its adaptive capacity in recovering to an acceptable level of service within a reasonable timeframe after being affected by disruptions.	Port infrastructure systems
Chen & Miller-Hooks (2012)	A network's capability to resist and recover from disruption or disaster.	Intermodal Freight Transportation networks
Ishfaq (2012)	The ability to maintain continuity in operations under disruptions.	Multi-mode transportation networks
Miller-Hooks et al. (2012)	Resilience involves both the network's inherent ability to cope with disruptions via its topological and operational attributes and potential actions that can be taken in the immediate aftermath of a disruption or disaster event.	Freight Transportation networks
Omer et al. (2012)	The ability of the system to absorb shocks as well as to recover from a disruption so that it can return back to its original service delivery levels or close to it.	Maritime transportation infrastructure systems
Tamvakis & Xenidis (2012)	The ability of a system to react to stresses that challenge its performance.	Transportation systems
Chen et al. (2013)	The ability of a system to absorb the consequences of disruptions to reduce the impacts of disruptions and maintain freight mobility.	International express logistics
Nursey-Bray et al. (2013)	The ability of a social or ecological system to absorb disturbances while retaining the same basic structure and ways of functioning, the capacity for self-organisation and the capacity to adapt to stress and change.	Ports

Reggiani (2013)	The capacity/ability of the system to absorb shocks without catastrophic changes in its basic functional organisation	Transportation networks
Baroud et al. (2014)	A function of the extent of loss experienced at the time and the speed at which the system recovers.	Inland waterway transportation networks
Chang et al. (2014)	The ability to absorb shocks while maintaining function.	Transportation infrastructure
Becker & Caldwell (2015)	The ability of a system to absorb disturbance and still retain its basic function and structure.	Seaports
Wang (2015)	The quality that leads to recovery, reliability and sustainability.	Transport planning
Zhang et al. (2015)	Resilience accounts not only for the network's inherent coping capacity but also its ability to adapt post-event efficiently.	Transportation networks
Hosseini & Barker (2016)	The ability to predict, adapt and/or quickly recover from a disruptive event.	Inland waterway ports
Lam & Bai (2016)	Resilience is the ability to tackle unexpected disturbances across the supply chain.	Maritime supply chain
Chen et al. (2017)	The ability of the system, with the help of immediate recovery activities, to meet the transport demand, as well as to recover and ensure the persistence of the performance level at a rational cost within a limited period, when faced with disruptions to the network.	Container transportation networks
Loo & Leung (2017)	The ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events	Transportation systems
Zhang et al. (2018)	The ability to restore functionality and performance in response to a disruptive event.	Traffic networks

As summarised in the above table, there are a variety of definitions for the notion of resilience proposed, and some of them are similar, having overlaps with other relevant concepts such as reliability, vulnerability, robustness, and survivability. Even though the research foci of these studies are transportation systems, they are conducted from different perspectives. Some focus on the resilience of the whole generalised transportation system or network, while others concentrate on a specified segment like inland waterways and ports. Moreover, most of the definitions of transportation resilience are given either from a system or a network perspective. A careful review of definitions of resilience shows that there is no universal description of what the transportation resilience is, or what the standard definition of it should be.

2.4.2 Key Characteristics of Resilience

Different terms have been used to describe the resilience and its characteristics, including but not limited to vulnerability (e.g. Omer et al., 2012; Zhang et al., 2015), adaptability (e.g. Becker and Caldwell, 2015), robustness (e.g. Blockley et al., 2012), preparedness (e.g. Miller-Hooks et al., 2012), redundancy (e.g. Berle et al., 2011), response (e.g. DiPietro et al., 2014) and recovery (e.g. Adams et al., 2012; Ashok and Banerjee, 2014). It is quite often the case that the same term is explained from various perspectives and used in a variety of ways to address different requirements. Moreover, authors sometimes introduce new terminologies for similar concepts or use terms without clearly defining them. Currently, there are few studies analysing the similarity and difference of the application of such terms in the transportation area. Here, we extracted from literature those most commonly used terms when describing the features and connotations of resilience, as summarised below.

- Vulnerability

The increasing importance of vulnerability analysis has been evidenced by many previous research findings in various transport segments such as road networks (e.g. Jenelius et al., 2006), railway networks (e.g. Johansson et al., 2011), maritime transportation systems (e.g. Mansouri et al., 2010), as well as those from a higher level, such as comprehensive transportation systems (e.g. Zhang and Levinson, 2008) or integrated supply chain networks (e.g. Klibi and Martel, 2012). The vulnerability was defined as the susceptibility to damage or perturbation – especially where small damage or perturbation leads to disproportionate consequences (Blockley et al., 2012). Also, it was regarded as the property of a transportation system that may weaken or constrain its ability to endure, handle and survive threats and disruptive events that originated both within and outside the system boundaries (Asbjørnslett and Rausand, 1999).

- Adaptability

Adaptability (also known as adaptive capacity) is defined as one of the functions of a resilient system (Dalziell and McManus, 2004), which reflects its flexible ability to respond to new pressures (Fiksel, 2003). Similar definitions were presented by Pettit et al. (2010) as the ability to modify operations in response to challenges or opportunities. It has also been encompassed in the definition of resilient countries as a timely adaptation in response to a changing environment (World Economic Forum, 2013). Such definitions indicate that its main features lie in response to changes reflecting the dynamic nature of complex systems.

Adaptability and vulnerability have been considered in pairs in a few studies of resilience, e.g. Omer et al. (2012) and Wang (2015).

- Robustness

Robustness is the property of being strong, healthy and hardy (Blockley et al., 2012).Thus, it is generally defined as the ability to withstand or absorb disturbances and remain intact when exposed to disruptions (Faturechi and Miller-Hooks, 2014). In the construction of the conceptual framework for resilience, Steen and Aven (2011) considered robustness from a risk perspective as a two-dimensional combination of consequences and associated uncertainties, given the occurrence of an initiating event. In this context, it became an antonym of the vulnerability. Similar ideas can be found in the predictive measure taxonomy given by Cox et al. (2011).

- Flexibility

The flexibility of a system represents its ability to respond to shocks (Cox et al., 2011) and adjust itself to changes through contingency planning after disruptions (Faturechi and Miller-Hooks 2014a). It is also referred to as an ability to reconfigure resources (Berle et al., 2013) as well as to cope with uncertainties (Goetz and Szyliowicz, 1997). Due to its property to adapt to changing circumstances and demands (Chen and Miller-Hooks, 2012), it has been considered as the same as adaptability in some research (e.g. Faturechi and Miller-Hooks, 2014) in terms of measuring the performance of a system. As such, connotations of flexibility are opposite to that of robustness which emphasises the ability to endure these changes rather than adapt to them.

- Reliability

Being a crucial parameter of resilience (Wang, 2015; Baroud et al., 2014), reliability is generally defined as the probability that a network remains operative given the occurrence of a disruption event (Faturechi and Miller-Hooks, 2014). In this way, reliability to some extent is a measure for the post-disaster performance of a system. However, Barker et al. (2013) suggested that reliability decides a system's performance during the time period before the strike of an external disturbance, in which, it becomes a kind of attribute describing the pre-disruption performance of a resilient system (Shinozuka et al., 2004), and it is able to provide a baseline for the performance of service when the system operates at the stable state (Baroud et al. 2014).

- Recoverability

Recoverability has been discussed the most in the research on transportation resilience. It is defined as the ability of a network to recover functionality in a timely manner (Baroud et al., 2014). Instead of using the concept of “recoverability”, similar expressions can be found such as “recovery”, and “the ability to recover”. They are regarded as an important feature of secure and highly functioning transport networks.

- Redundancy

Redundancy indicates the ability of certain components of a system to take over the functions of failed components without adversely affecting the performance of the system itself (Haimes, 2009). In brief, it reflects the availability of alternative choices (Tukamuhabwa et al., 2015), through which parallel systems can be utilised to provide alternative operations in case of failures of the original one (Omer et al., 2012). In the context of transportation, redundancy is also viewed as the existence of optional routes between origins and destinations, which can help to mitigate adverse impacts on transportation systems from disasters. It is commonly accepted that the more redundancy a system has, the more resilient it will be (Fiksel, 2003), leading to a longer term of development (O’Kelly, 2015). The redundancy of routes is of great significance, especially in emergency situations. However, it should not be ignored that over-pursuit of redundancy will inevitably lead to an exorbitant cost.

- Survivability

Survivability is generally defined as the ability to withstand sudden disturbances while meeting original demands (Faturechi and Miller-Hooks, 2014a). Survivability techniques have been considered as access to mitigating the vulnerability of a network or system (e.g. Baroud et al., 2014; Barker et al., 2013). Thus survivability approaches can help to reduce the adverse impacts on a system from unexpected disruptive events.

- Preparedness

Preparedness refers to the preparation of certain measures before a disruption, and it enhances the resilience of a system by lessening potential negative impacts from disruptive events. It can be subdivided as emergency preparedness and response preparedness, being favoured by different industrial sectors (Berle et al., 2011). In the framework of disaster management proposed by Altay and Green (2006), preparedness is the second step, and it belongs to the pre-disruption stages (which are mitigation, preparedness, response, and recovery).

- Resourcefulness

Resourcefulness is defined as the availability of materials, supplies, and crews to restore functionality in a study of transportation resilience (Adams et al., 2012). In another research relating to the transport security policy, resilience was discussed in terms of its applications at the economic level. In that context, resourcefulness was treated as one of the stabilizing measures in terms of resilience (Reggiani, 2013). In a review work of resilience analysis of engineering and infrastructure systems, Francis and Bekera (2014) defined resourcefulness as the level of preparedness in effectively resisting an adverse event.

- Responsiveness

Klibi et al. (2010), described responsiveness as the capability of a supply chain system to respond positively to disturbances, and the development of this capability can be either redundancy or flexibility based. It provides a barrier against threats and risks, so as to increase the expected value of supply chain networks (Klibi et al., 2010). Thus, responsiveness is regarded as an important factor contributing to the resilience of supply networks (Klibi & Martel, 2012). Similar to redundancy, responsiveness factors of a system may also increase the costs although it is able to improve the service level of a system.

- Rapidity

Rapidity is a well-studied concept in the “resilience triangle”, a framework that has been applied in civil infrastructure for decades. It contains a hidden meaning of recovery, but with an emphasis on the speed to recover.

2.4.3 Research Methods Applied in Resilience Studies

The dominant research methods considered in the literature review are surveys, case study, conceptual work, mathematical modelling, simulation and others (e.g. Wacker, 1998; Woo et al., 2011; Tukamuhabwa et al., 2015). A survey aims to study the sampling of individual units on a specific topic. It is a commonly used method to collect required information which generally can be done through the questionnaire and the interview. A case study is an in-depth investigation of a particular person, community or situation. Research conducted through surveys or case studies belongs to empirical research (Tukamuhabwa et al., 2015). The conceptual work category here is rather broad, including analysis on concept issues such as definitions, properties, theoretical framework and conceptual modelling. While, being different to the conceptual modelling, papers under mathematical modelling refer to those applying mathematical concepts and language to describe and represent objective reality. A simulation method is used to study the operation of a real-world or a theoretical process/system under various pre-set circumstances for different purposes (e.g. numerical testing, observing behaviour, optimising performance, or exploration of new states). The category of ‘others’ encompasses archival analysis, literature review, and perspectives from industries, etc. The number of investigated papers with respect to different research methods is depicted in Figure 2.5. Empirical studies are further analysed in Table 2.3 in order to provide helpful insights into the potential applications of transportation resilience in practice.

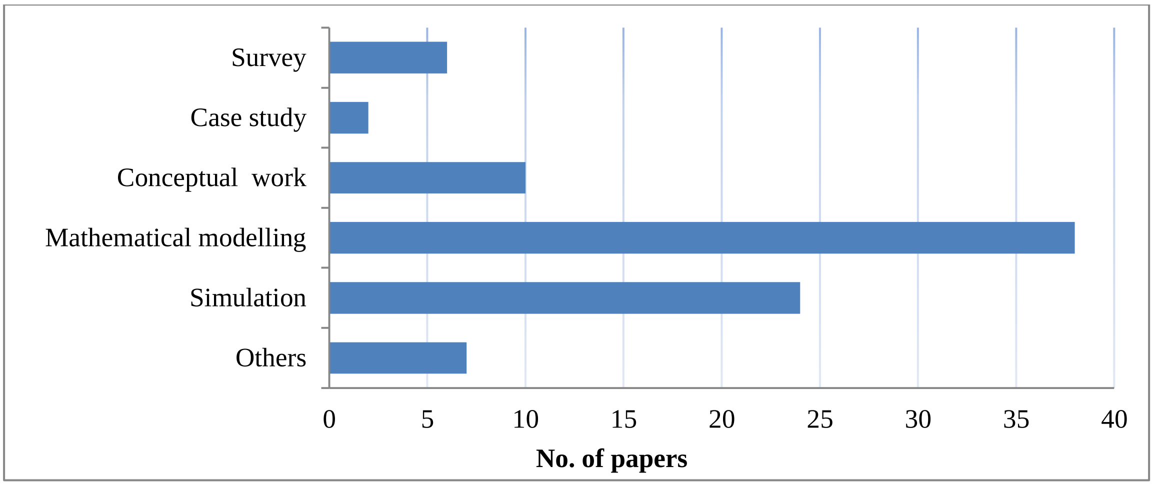


Figure 2.5. Distribution of investigated papers by research methods

Table 2.3. Overview of empirical research on transportation resilience

Author(s)	Year	Country	Methodology	Application fields	Research objectives	Disturbances
Gomes et al.	2009	Brazil	Survey	Helicopter transportation	To discover transport system resilience in terms of workload demands and economic pressures.	Constraints of daily operations
Berle et al.	2011	USA & Panama	Survey	Maritime transportation	To provide matrices of the key functions of maritime transportation systems.	Failures
Adams et al.	2012	USA	Case study	Road transportation	To present a set of criteria to qualify the computed resilience measures.	Disruptive weather events
Nursey-Bray et al.	2013	Australia	Survey	Port	To evaluate and learn from practices relating to climate change preparedness within Australian ports.	Climate change
Bruyelle et al.	2014	UK	Case study	Metro system	To propose improvements to the design of metro systems, and to improve the management of emergency situations.	Terrorist attacks
Chang et al.	2014	Canada	Survey	Infrastructure system	To develop a practical approach to characterise communities' infrastructure vulnerability and resilience in disasters.	Earthquake & flood
Becker et al.	2015	USA	Survey	Port	To investigate how port stakeholders consider the impacts of storms on seaport's vulnerability and address the concerns	Storm
Becker & Caldwell	2015	USA	Survey	Port	To identify strategies which can improve the port's resilience from a practice perspective.	Storm

Based on the above review, it can be concluded that a resilient MCSC is well-organised with the ability to maintain its basic structure and function, and recover to a required level of service/performance within an acceptable time and costs after the failure of one or more components.

2.5 Research gaps

Although the risk assessment of the MCSCs has been given attention by academics and practitioners, the research of comprehensive performance evaluation of MCSCs from a systematic view is still a fertile area emerging from growing challenges and the fact that a very limited amount of research actually specifies this issue in literature, as well as in practice. The specific research gaps are concluded as follows:

(1) Identification of risk factors is an essential step to produce a list of risks in order to manage them well. Although some good insight has been provided by these studies in terms of the identification of risk factors in the container shipping industry, special attention is usually drawn on some particular aspects such as human factors (e.g. Lu and Shang, 2005; Yang et al., 2013a; Xi et al., 2017), operational factors (e.g. Chang et al., 2014; Yang et al., 2013b; and 2014), and shipping security-related political factors (e.g. Yang, 2010; Yeo et al., 2014). Thus, risk factors were identified at segment levels, and the attention that is given to systematic identification of all possible risk factors faced by an MCSC is scarce. Moreover, the increasing complexity of modern MCSCs has given birth to some emerging risk factors which have been seldom investigated in previous studies such as climate change and refugee immigrant issues. Their influence (especial long-term influence) on MCSCs also deserves attention.

(2) A broad literature review shows that most of the previous studies on supply chain risk assessments paid special attention to the occurrence probability of an event and the severity of the consequences (e.g. Manuj and Mentzer, 2008; Vilko and Hallikas, 2012; Chang, Xu and Song, 2014), leaving the other features of risk not being fully explored during the risk analysis of complicated supply chain systems. Relying only on two basic risk parameters (i.e. probability and consequence) will inevitably lead to the loss of useful information in risk analysis, and more importantly, it cannot really distinguish the safety levels of different risks when the investigated chains are large and complicated, presenting hundreds of different risk events. Moreover, the existing risk assessment methods more or less showed some drawbacks in the industrial applications (e.g. Gaudenzi and Borghesi, 2006; Pujawan and Geraldin, 2009; Samvedi, Jain, and Chan, 2013), especially for the quantitative analysis of maritime risks under

a highly uncertain environment. This calls for more suitable risk assessment method that is able to process different types of information from multiple sources in a consistent manner, to deal with the uncertainties in risk inputs, and to provide accurate results while maintaining a certain degree of visibility, transparency, as well as easiness to operate.

(3) The majority of the current research focused on the risk management of a separated segment of MCSCs (e.g. port operation and maritime transportation), without the consideration of the specific role that the investigated part plays in the whole supply chain system (Soner, Asan and Celik, 2015; Alyami et al., 2016; Cui, Wan et al., 2017; Wang and Ma, 2017; Yan et al., 2017). This may lead to the suboptimal solutions in terms of risk prevention and control, as it is often the case that the riskiest component within a system does not necessarily mean that it also has the most impact on the system performance. Thus, both the local risk condition of an MCSC and its impact on the whole supply network need to be considered in order to obtain more rational and accurate results.

The identified research gaps indicate the valuable points of additional work that are presented below:

- A holistic framework of risk factor identification

A holistic framework of risk factor identification is required to capture a more exhaustive variety of risks under a broader context and extends the risk factor identification and analysis from segment to system levels.

- Advanced risk assessment methods under uncertain environment

Advanced and novel risk assessment methods need to be able to process different types of information (e.g. quantitative and qualitative, subjective and objective) from multiple sources in a consistent manner and to provide accurate results while maintaining a certain degree of visibility, transparency, as well as easiness to operate.

- Comprehensive and systematic performance evaluation methods

It is important and necessary to take into consideration the weight and influence of each MCSC with the entire supply network so as to realise a comprehensive performance evaluation of MCSCs from a systematic perspective.

CHAPTER 3 - IDENTIFICATION OF RISK FACTORS INFLUENCING THE PERFORMANCE OF MARITIME CONTAINER SUPPLY CHAINS

Summary

In this chapter, the definition and classification of supply chain risks are comprehensively reviewed in order to provide a reference for the understanding and identification of risk factors in MCSCs. Based on the novel framework for risk classification proposed in this chapter, distinct risk factors in MCSCs, and those of general supply chains are identified and validated by incorporating domain experts' perceptions. Moreover, an empirical study on the assessment of all identified risk factors is conducted using the data collected from a large-scale questionnaire survey. The survey was carried about by different groups of maritime stakeholders, who own the world leading commercial container fleets and container ports. By doing so, this chapter tries to extend the risk analysis from segment to system levels and realises the hazard identification and risk analysis of different MCSC nodes (e.g. ports) and links (e.g. multi-modal transport) on the same plate so that they can be better understood and managed from a supply chain perspective. Those risk factors with relatively higher importance are selected for further assessment in the next chapter.

3.1 Introduction

Various kinds of risk factors may appear at different stages of container shipping operations, such as fluctuation of fuel price (Notteboom, 2006), dynamic customer demands (Das and Dutta, 2013), political instability (Vilko et al., 2016), and transportation accidents (Vernimmen et al., 2007), which will result in different types of risks that hinder the safe and efficient operations of an MCSC. For instance, on 21 February 2010, a container ship of 657 TEU capsized and foundered after leaving the Port of Vieux-Fort on St Lucia in the Carribean. It was investigated that the accident was caused by insufficient stability resulting from the improper loading and stowage of containers (RINA, 2017). A post-Panamax container ship called MOL Comfort broke in two due to bad weather on its way from Singapore to Saudi Arabia, losing 4,382 containers in the accident on 17 June 2013 (Gaidai et al., 2018). On 12 August 2015, a series of explosions occurred at a container storage station at the Port of Tianjin, China. Altogether 173 people were killed, and 797 were injured in the accident, causing a direct economic loss of 6.86 billion Chinese Yuan (equivalent to more than 1 billion USD), and severe environmental damage as well (BBC, 2015). The above evidence shows that risk studies of MCSCs are necessary and urgent. However current literature reveals that most hazards and/or risk factors are still dealt with at individual segment levels of MCSCs (e.g. port and container shipping), leading to their importance not being measured at the same plate and safety resources not being rationalised from a global system perspective. It shows there is a research gap to be filled, particularly given the increased number of container transport accidents along with the fast growth of containerised multi-modal transportation in MCSCs.

Analysis of risk factors is critical to the success of effective risk management, as it can help identify the hazards/threats a company is facing with priority, understand where a risk may emanate from, and evaluate how much a company is exposed to uncertainties, so that rational mitigation strategies can be developed to ensure the performance of a whole supply chain. This work for the first time uses a uniform scale to evaluate the existent and emerging risk factors influencing MCSCs as a whole on the same measurement scales so that they can be better managed from a systematic level.

The remainder of this chapter is organised as follows. Section 3.2 reviews the literature concerning the classification of supply chain risks. Section 3.3 introduces the methods used in this study for the identification, measurement and validation of risk factors. A novel framework for risk classification is proposed in Section 3.4, along with all risk factors identified based on the proposed classification framework. Section 3.5 describes empirical investigation and analysis of risk factors based on the descriptive statistical analysis and a risk matrix method. The research results, implications, and this chapter are concluded in Section 3.6.

3.2 Review of Classification of Supply Chain Risks

As the start point of the traditional risk management process, risk classification and identification have been extensively discussed within the context of supply chains. The classification process clarifies the relationships among different risk sources and the relevant dimensions of potential disruptions in a supply chain as well, providing a basis for the identification of risk factors and the follow-up assessment. Various ways of sorting risk sources coexist. One of the most basic and straightforward ways is to classify risks into two categories, which are internal and external risks. For instance, Kumar et al. (2010) argued that internal risks arose due to improper coordination among different levels, including factors like demand, production, and supply risks. External risks usually resulted from interactions between a supply chain and its environment, comprising factors such as terrorist attacks, natural hazards, and exchange rate fluctuations. In a review of enterprise risk management, Olson and Wu (2010) pointed out that internal risks contained those from available capacity, internal operations, and information systems, while external risks evolved from nature, political systems, competitors, and markets. Another similar method was to classify risks on their endogenous and exogenous origins, depending upon whether the risk source lay within or beyond the supply chain boundaries. Examples were found in Trkman and McCormack (2009), Wagner and Neshat (2012), and Vilko et al. (2016). Other binary classification methods included those considering, for example, operational and disruption risks (Tang 2006), quantitative and qualitative risks (Svensson, 2000), macro- and micro-risks (Ho et al. 2015), and systematic and non-systematic risks (Baghalian et al., 2013). It is worth noting that, in general, different interconnected organisations/companies are involved in a supply chain. Therefore, endogenous risk sources were further distinguished as "beyond company borders" and "corporate-wide" sources by Götze and Mikus (2007). In this way, supply chain risks can be divided into three categories (Jüttner et al., 2003), which were environmental risks, network-related risks, and organisational risks. Organisational risks were those that lay inside the organisational boundaries, whereas network-related risks were from interactions between organisations and other partners within the same supply chain. Environment risks comprised uncertainties existing in the external environment. An illustration is shown in Figure 3.1. Another classification of supply chain risks which had also attracted a lot of attention addressed risk factors from the perspective of three main logistics flows, namely, physical/material flow, information flow, and financial/payment flow (Chopra and Meindl, 2010). On the basis of Tang's (2006) research, Tang and Musa (2011) identified supply chain risks in terms of material, information and financial flows. In the study, material flow risks were investigated from the stages of the source, production and delivery. Financial flow risks involved exchange rate risk, price and cost risk, financial strength of supply chain partners, and financial handling and practice. Risk factors related to information flows lay in information accuracy, information system security and disruption, intellectual property, and information outsourcing. In a similar way, a risk analysis for container shipping operations was carried out by Chang, Xu and Song (2015), who considered that risk elements associated with information flow were information delay, inaccurate information, and IT failure, whereas main risk elements in a physical flow contained transportation delay and cargo/asset loss or damage, and risk elements related to a payment flow included currency exchange, payment delay, and non-payment. These risk elements were further analysed, and finally, 35 risk factors were identified. Additional risk classification methods were found in previous studies that categorised supply chain risks according to their influence on supply chain performance, controllability of risks, roles within a supply chain, and uncertain parameters in relation to supply chain activities (Cavinato, 2004; Bogataj and Bogataj, 2007; Blackhurst et al., 2008; Manuj and Mentzer, 2008; Tang and Tomlin, 2008; Tummala and Schoenherr, 2011; Samvedi et al., 2013; Martino et al., 2017), to name just a few.

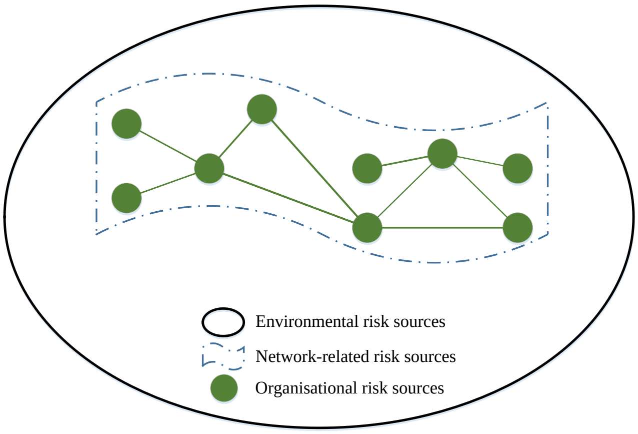


Figure 3.1. Illustration of risk sources in supply chains
Source: adapted from Jüttner, Peck and Christopher (2003)

However, most of the research related to the risk identification, assessment, and management is usually conducted either from a perspective of the entire supply chain, or with focus on a specific function or a part of a supply chain (such as container terminal operations, container shipping, or land transportation) without considering the influence from its upstream/downstream within the whole supply chain from a systematic viewpoint. By incorporating multiple dimensional risk classification methods, MCSC risks are classified into two main groups composed of five major risk sources (Zhang et al., 2014). Refer to Section 3.4 for detailed information.

3.3 Methodology for Data Collection and Analysis

In this section, a detailed explanation of data collection and analysis methods applied in this chapter will be presented associated with the risk analysis process. To identify and understand the risk factors existing in the MCSCs, qualitative methods are involved to collect and examine risk data, along with justification due to the lack of standardised statistics data for most of the risk factors and a variety of uncertainties existing in daily operations of MCSCs. The first sub-section introduces the data collection methods in the phase of risk factor identification and validation. The second sub-section describes the data collection methods in the measurement of verified risk factors. The last sub-section introduces the data analysis methods with emphasis on the risk matrix approach, and the method for the validation of collected data is also discussed in this sub-section.

3.3.1 Data Collection Method in Risk Factors Identification and Validation

3.3.1.1 Identification of Risk Factors

Several common methods for systematically identifying risk factors are the flowchart method, review of accident statistics, analysis of corporate records and documents, risk questionnaire, and risk surveys (Yang, 2010). Waters (2007) also suggested other tools that can be used in the risk factor identification including document review, interviews, and group meetings.

Generally, the identification of risk factors can be separated into two distinct phases, i.e. initial risk factor identification, and on-going risk factor identification. In the first stage, a framework for risk factor classification is proposed from a systematic perspective. Based on that, all possible risk factors related to each aspect of an MCSC system are identified through reviewing relevant literature (A detailed introduction of the framework and all identified risk factors will be presented in Section 3.4). The second step is necessary as it helps to 1) identify new risk factors which did not previously arise, 2) recognise changes in existing risk factors, and 3) exclude risk factors which did exist but now do not directly influence our system anymore. Several studies have also used a literature review to identify risk factors, e.g., Yang (2011) and Chang, Xu and Song (2014).

3.3.1.2 Validation of Risk Factors

Given the difference between academic studies and industrial applications, as well as potential ambiguities when presenting those risk factors, it is necessary and helpful to involve judgements from experts who are most familiar with conditions to validate the identified risk factors. Based on the review of previous studies, considering the complex degree of MCSC systems and the reliability of data collected from the experts' survey, this thesis uses the Delphi method to validate the identified risk factors and explore other potential ones.

The Delphi method is a structured communication technique which relies on the results of questionnaires sent to a panel of experts. Normally, several rounds of questionnaires need to be sent out, and an anonymous summary of responses from previous rounds as well as the reasons they provided for their judgements are aggregated and shared with the group after each round. The experts are allowed to revise their earlier answers in subsequent rounds according to the replies of other members of the panel. Since multiple rounds of questions are undertaken, and the panel is advised on what the group thinks as a whole, the Delphi method is believed to be able to obtain a reliable and consistent response to a problem from a group of experts through consensus. It is well suited, as a research instrument, to model incomplete knowledge (Skulmosji et al., 2007). It thus especially works well in this study given the uncertainties of various risk factors and the complexity of an MCSC system. As a flexible research approach, Delphi-based methods have been successfully used in industrial risk management, particularly in the identification of risk factors where subjective inputs are largely depended on (e.g. Chapman, 1998; Markmann et al., 2013; Qureshi et al., 2014).

Different Delphi processes have been introduced and applied (Linstone and Turloff, 1975). According to the specific research background and objectives in our research, a brief flow chart of the main processes of the Delphi method is shown in Figure 3.2, while the specific steps applied in this study are introduced as follows. The Delphi expert survey started in January 2017, and it took three months to reach the final results of accepted consensus.

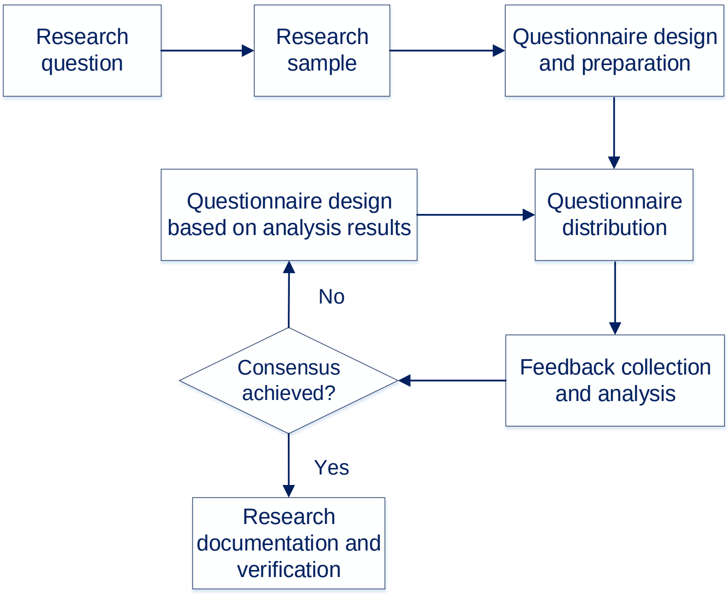


Figure 3.2. Flowchart of the Delphi process

Source: author

- Step 1: Define the problem

Research questions are generally derived in accordance with the main research purpose. In this study, we aim to propose a classification framework for the identification of risk factors in MCSCs from a systematic perspective, and to identify relevant risk factors and evaluate their risk levels. Thus, two issues that need to be dealt with through the Delphi method are 1) establishment of a classification framework, and 2) exploration and validation of risk factors in an MCSC. It is worth noting that before all questions are finalised for the formal Delphi expert survey, a pilot study is firstly conducted to identify the possible ambiguities and vagueness in the designed questions. Based on the results and comments of participants in the pilot survey, the invitation letter of the survey is improved, and the layout of the questionnaire is modified to provide a clearer instruction.

- Step 2: Research sample

Selecting research participants is a critical component of the Delphi method since it is their expert opinions that contribute to the final outputs of the Delphi survey (Skulmosji et al., 2007). In terms of the sample selection of the Delphi survey in this study, 28 experts from different countries were contacted. Ten of them from eight organisations replied to the authors within the given time window (from 2 to 29 January 2017), showing their willingness to serve as a member of the Delphi expert group in this work. The profile information of selected participants is listed in Table 3.1.

Table 3.1. Profile of participants in Delphi expert group

No	Type of organisation	Year of working	Department/ professional area	Position	Country
1	University*	32	International shipping business management	Professor	China
2	University*	26	Supply chain management marketing and operations	Professor	UK
3	Port authority	21	Port safety and operation management	Senior officer	Saudi Arabia
4	Maritime authority	27	Maritime transportation, environment, and energy	Senior advisor	USA
5	Maritime authority	33	Maritime safety and waterway traffic accident investigation	Senior marine investigator	China
6	Shipping company	25	Contract logistics	Senior manager	China

7	Shipping company	27	Supply chain development and project management	Senior manager	Singapore
8	Shipping company	27	Marketing and sales	Vice present	China
9	Shipping company	29	Marine operating centre	Senior captain	China
10	Shipping company	26	Container ships more than 10,000 TEU	Senior captain	China

* Both of them also had rich working experience in the container shipping industry.

A single panel of experts with different backgrounds (for example, academics, industry experts, and administrators) was selected in this study for the completeness of the judgements from different stakeholders' perspectives. Their professional areas are balanced in the Delphi expert group, thus being able to reasonably represent a general understanding of an MCSC and provide reliable outputs. The ten participants are from one university in China, one university in the UK, one port authority in Saudi Arabia, one maritime authority in the USA, one maritime authority in China, one shipping company in Singapore, and two shipping companies in China. Besides, it is worth noting that these three shipping companies are among the top ten container shipping companies in the world. In addition, they all have rich working experience in container shipping or related industries/research, taking a relatively senior position in the field.

- Step 3: Round one Delphi expert survey

In the first round survey, some semi-structured questions are developed to collect opinions on the rationality of the risk factor classification structure and the identified risk factors. We can then figure out whether the structure of the framework for risk factor categorisation is appropriate, whether these identified risk factors really exist, and whether there are any other risk factors that should also be considered. The questionnaire is distributed to the ten Delphi participants separately, and they are given four weeks to return their comments. During the defined period, they can revise their responses at any time, and they are also encouraged to attach reasons why these changes are made. The questionnaire for the first round Delphi expert survey is listed in Appendix One.

- Step 4: Round two Delphi expert survey

All opinions of the participants from the first round survey are summarised, based on which some modifications are made to the initially proposed framework and identified risk factors. The main changes lie in the structure of the framework for risk factor classification. Besides, some risk factors are modified/deleted, and new ones are added. The round-two questionnaire is developed according to the responses from round one and then released to each participant in the Delphi expert group.

In the second round survey, the participants are first given the opportunity to check if their responses in round one indeed reflect their opinions and then asked to evaluate the extent to which they agree with (if not agree, explain the reason) the changes made in the previous survey in this round. This process may be repeated several times until the convergence on the agreement degree of the participants is obtained. A time limit of two weeks is set for the second round survey since all participants had already been familiar with the study, and this process would not take as much time as the previous one. Again, a similar process of analysis is conducted based on all responses from the second round survey.

- Step 5: Round three Delphi expert survey

The statements that do not reach the consensus from the last round will be reformulated based on panel comments and included in the next round. The round-three questionnaire is developed according to the responses of all participants from the second round and then is distributed to each participant. Again, these participants are given the opportunity to change their answers and to comment on the emerging and modified risk factors according to other participants. In this study, the round three Delphi expert survey is the final one. According to their feedback, the consensus from the majority of participants in the expert panel on the structure of the framework for risk factors classification and the identified risk factors is reached.

- Step 6: Verify and document research results

For the validation purpose, a revision report generated from the three-round Delphi survey is sent to each Delphi expert. The revision report presents the difference between the original statement and the modified one in terms of the structure of the framework for risk factor classification and the identified risk factors, along with the reasons for all the modifications (as shown in Appendix Two). No more modification is needed according to the experts' feedback, revealing an acceptable consensus level of their opinions on the results.

In this study, the research steps are developed based on the distinct phases introduced by Linstone and Turloff (1975) which have proven to be reliable over the years. Moreover, a sufficient number of participants who have an academic, industrial or administrative background are chosen and involved in a three-round Delphi survey. All the participants have rich working experience (more than twenty years) in container shipping or related industries/research areas with a senior position in their fields. In addition, a pilot survey is conducted to improve the quality of the questionnaire. Thus, the validity and reliability of the Delphi expert survey are guaranteed.

3.3.2 Data Collection Method in Risk Factors Measurement

Measurement of risk factors is usually conducted in a quantitative way to provide the reference needed for decision making, and two parameters that have widely been used for quantifying risks are 1) the occurrence likelihood of a risk event, and 2) the consequence severity when it occurs. However, it is worth noting that likelihood and consequence are just two considerations among many factors when conducting a risk analysis in practice (Waters, 2007).

In this chapter, a questionnaire survey with a Likert scale is used to gather information in the MCSC domain due to the lack of accurate industry-specific risk data. Based on the results of the Delphi expert survey, the questionnaire is constructed comprising of six major parts: the respondents' profile, the measurement of risk factors associated with society, the measurement of risk factors associated with natural environment, the measurement of risk factors associated with management, the measurement of risk factors associated with infrastructure and technology, and the measurement of risk factors associated with operations (see the whole questionnaire in Appendix Three). The questionnaire is designed to elicit expert opinions on the identified risk factors in terms of occurrence likelihood and consequence severity. In order to collect data suitable for a 7×4 risk matrix as suggested by IMO (2002) in maritime-related research, different categories of occurrence likelihood and consequence severity are applied in this thesis, illustrated as follows.

- The occurrence likelihood

The occurrence likelihood of a risk factor means how likely it is that the risk factor will occur, represented by the frequency of it occurring at a certain time period or the probability it occurs, according to the certain circumstance under investigation. Thus, the value of occurrence likelihood is located between 0 and 1, where 0 indicates that it will never happen while 1 means it will definitely happen. However, it is not always possible to propose an accurate numerical value for the occurrence likelihood of each risk factor in practice, and thus the linguistic terms are usually used to describe the occurrence likelihood. In this thesis, a questionnaire with a

Likert seven-point scale is used to collect the occurrence likelihood of a risk factor within the MCSCs. 1, 2, 3, 4, 5, 6, and 7 are used to represent the likelihood of occurrence of a risk factor in an increasing order, in which 1 is for “Extremely Rare”, 2 for “Rare”, 3 for “Unlikely”, 4 for “Possible”, 5 for “Likely”, 6 for “Frequent”, and 7 for “Very Frequent”. The definition of the occurrence likelihood of a risk factor is further illustrated in Table 3.2.

Table 3.2. Definitions of the occurrence likelihood of a risk factor (Alyami et al., 2014)

Likelihood	Likert scale	Definition
Extremely Rare	1	Has never or rarely happened
Rare	2	Not expected to occur for a few years; May only occur in exceptional circumstances
Unlikely	3	Trivial likelihood, however, could occur at some time
Possible	4	Might occur at some time; Expected to occur every few months
Likely	5	Will probably occur in most circumstances; Expected to occur at least monthly
Frequent	6	Expected to occur at least weekly
Very Frequent	7	Can be expected to occur in most circumstances; Occur daily

- The consequence severity

The consequence severity refers to the magnitude of the possible effect when a risk event occurs. It can be measured from a variety of aspects such as health impacts, service interruptions, reputation issues, objective failures, etc. For example, the consequence of a risk event in engineering domains is usually estimated involving injuries/fatalities, property loss, and/or environmental damage. While, in the risk management of a supply chain, the consequence is normally measured considering time, cost, and quality (Vilko and Hallikas, 2012). To describe the degree of consequence, different categories of linguistic terms have been proposed such as “no safety effect, minor, major, hazardous, and catastrophic” (Cox, 2008), “negligible, marginal, moderate, critical, and catastrophic” (Yang, Bonsall and Wang, 2008), and “low impact, medium impact, and high impact” (Alyami et al., 2014). In this thesis, a questionnaire with Likert four-point scale is used to collect judgements on the consequence severity of each risk factor, and the four linguistic grades are represented with a score of 1, 2, 3, and 4, respectively. The definition of different levels of risk consequence is illustrated in Table 3.3.

Table 3.3. Definitions of the consequence severity when a risk factor occurs (Hu et al., 2007)

Consequence severity	Likert scale	Definition
Minor	1	Cause some inconvenience with minor impacts such as small cost/schedule increase.
Moderate	2	Cause some disruptions with medium impacts such as moderate cost increase, delay, and minor environmental damage.
Severe	3	Cause some disruptions, or sometimes failures with severe impacts such as major cost increase, major environmental damage or injuries
Catastrophic	4	Cause complete and irrecoverable failures (thus the minimum requirements cannot be achieved), long-term environmental damage, or death

The questionnaires for the measurement of risk factors are developed in English at the early stage and translated into Chinese. The target sample for the questionnaire survey is selected from the top ten shipping companies in China (and their branch companies worldwide), shipping agencies, freight forwarders, maritime safety administrations, port authorities, and other organisations related to the container shipping industry. Several questionnaires are sent to the relevant departments of each company in person or through emails. The questionnaire is also coded to an online questionnaire via e-survey creator (https://www.diaochapai.com/survey2539536) to ensure that more validated participants can be involved in the questionnaire survey easily.

3.3.3 Data Analysis and Validation

3.3.3.1 Descriptive Statistics Analysis

After having collected all data needed for the measurement of risk factors, a descriptive statistics analysis will be conducted to present the respondents' profile of the questionnaire. Descriptive statistics analysis is a method to quantitatively describe or summarise features of a collection of data, and present the processed data in the form of a table or chart, so that the meaningful information we need can be revealed. Attributes that are commonly used in descriptive statistics analysis include, but are not limited to, the minimum and maximum values, standard deviation (SD), mean value, percentage, and frequency. Moreover, there are also tools that can be used to present the statistics in a more intuitive way, such as histogram, polygon, pie chart, etc. In this thesis, the percentage, mean value, and standard deviation are the three main features used in the descriptive statistics analysis, and these features are shown by using tables.

3.3.3.2 Risk Scale Analysis

- Risk calculation

In practice, it is necessary and important to know which risk factors are the most serious so as to optimise the risk management with limited resources. The level of risk can be calculated by the following formula (Manuj and Mentzer, 2008; Vilko and Hallikas, 2012; Chang, Xu and Song, 2015):

$$Risk = probability \times consequence \qquad \text{Eq. 3.1}$$

In which, the *probability* may also be presented as frequency or likelihood, while the *consequence* may be expressd using severity, impact, or loss. In this thesis, the risk scale of each risk factor in MCSCs is defined as:

$$Risk = occurrence\ likelihood \times consequence\ severity \qquad \text{Eq. 3.2}$$

As a key step to perform risk analysis, calculating the risk level for each risk factor over all respondents enables the comparison of their relative importance. Given that the risk level is determined by the likelihood and the consequence, there are two main methods that can be considered to calculate the risk level with multiple expert judgements (Chang, Xu and Song, 2015). The first method is to multiply the average value of likelihood over all respondents with that of consequence for each risk factor, while, the second method is to average the risk levels of each risk factor obtained from each individual over all the respondents.

Three pieces of resulting information can be obtained from the first method, which are an average likelihood, an average consequence, and the risk level calculated based on the previous two. These results are easy to be applied and mapped in the risk matrix as all three are necessary. However, one major disadvantage of this method lies in the way of approaching the final risk level of each risk factor. In the first method, the likelihood from one respondent is multiplied by the consequence from other respondents, which may distort the results. Compared to that, the second method is more reliable and reasonable in terms of the calculation of risk level, as the risk level is obtained firstly considering each respondent's judgement independently, and then finalised by averaging the results from all respondents. However, it suffers from the deficiency that it only provides the overall results of risk levels without the corresponding information on risk likelihood and consequence. Therefore, a risk matrix approach is applied in this thesis in order to benefit from both of the risk calculation methods by introducing logarithms into the measurement of likelihood and consequence.

- Risk matrix

A risk matrix has been widely used in various areas to evaluate risk factors in a quantitative way. A risk matrix table is composed of two dimensions - one vertical dimension consisting of several likelihood categories, and one horizontal dimension made up of several consequence categories. In this thesis, seven categories are developed for likelihood, and four for consequence, which are associated with the Likert scales set in the risk factor questionnaire, as shown in Table 3.2 and Table 3.3, respectively. Based on that, a 7×4 risk matrix can be constructed. As recommended by the International Maritime Organization (IMO, 2002), the likelihood and consequence indices are defined on a logarithmic scale to facilitate the ranking and validation of ranking. Consequently, Eq. 3.3 can be obtained.

$$\text{Log}\ (\textit{Risk}) = \text{Log}\ (\textit{occurrence likelihood}) + \text{Log}\ (\textit{consequence severity}) \qquad \text{Eq. 3.3}$$

Then, the Risk Index (*RI*) is established by adding the Likelihood Index (*LI*) and Consequence Index (*CI*) (Wang and Foinikis, 2001).

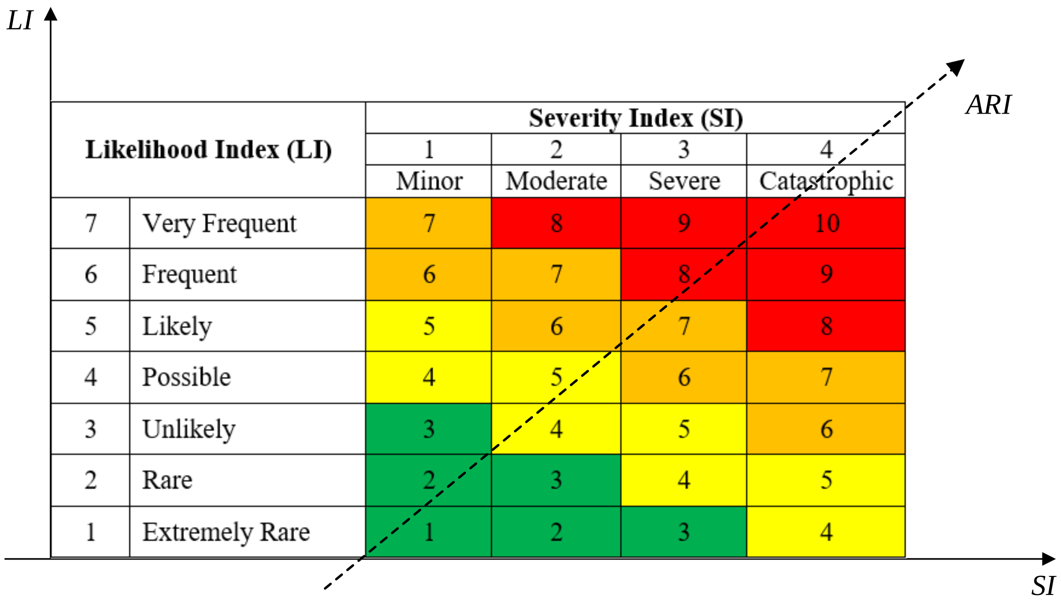
$$\boldsymbol{R}\textit{isk}\ \boldsymbol{I}\textit{ndex} = \boldsymbol{L}\textit{ikelihood}\ \boldsymbol{I}\textit{ndex} + \boldsymbol{S}\textit{everity}\ \boldsymbol{I}\textit{ndex} \qquad \text{Eq. 3.4}$$

In this way, the average risk level of each risk factor obtained from either of the above-mentioned methods will be the same due to the associative law of addition (which can be seen from Eq. 3.5.). To classify the risk levels and quantitatively compare the importance of each risk factor, the Average Risk Index (*ARI*) is defined in this paper, which can be calculated using Eq. 3.5.

$$\begin{aligned} ARI_r &= \frac{1}{N}\sum_{i=1}^{N} ARI_{ri} \\ &= \frac{1}{N}\sum_{i=1}^{N}(LI_{ri} + SI_{ri} - 1) \\ &= \frac{1}{N}\sum_{i=1}^{N} LI_{ri} + \frac{1}{N}\sum_{i=1}^{N} SI_{ri} - 1 \\ &= \overline{LI}_r + \overline{SI}_r - 1 \end{aligned} \qquad (r = 1,2,...,M;\ i = 1,2,...,N) \qquad \text{Eq. 3.5}$$

Where, M is the number of risk factors, and N is the number of the respondent. $\overline{LI}_r$ is the average Likelihood Index of the r^{th} risk factor, and $\overline{SI}_r$ is the average Severity Index of the r^{th} risk factor. LI_{ri} is the Likelihood Index of the r^{th} risk factor by the i^{th} respondent, while SI_{ri} is the Severity Index of the r^{th} risk factor by the i^{th} respondent. Both of them are obtained through questionnaires as described in Section 3.3.2.

According to the numerical risk outcomes, identified risk factors can generally be classified into three or four different risk categories (Markowski and Mannan, 2008). In this work, four risk categories are defiend to support a more flexible and reasonable decision-making process in risk management. The risk levels can be determined according to the *ARI* value of each risk factor. They are, a) low-risk level, in which $ARI \in [1, 4)$ and is coloured in green. Risk factors of this level have a minor impact on an MCSC which can be ignored, and thus no further action needs to be taken by managers; b) low-moderate level, $ARI \in [4, 6)$, in yellow colour; c) high-moderate level, $ARI \in [6, 8)$, in orange colour. Both levels belong to a moderate risk level, to which certain attention needs to be paid. According to the ALARP principle, risk reduction measures are needed until they are no longer reasonable according to the cost-benefit analysis; and d) high-risk level, where $ARI \in [8, 10]$, and it is represented in red colour. Risk factors falling into this region have high occurrence likelihood with serious consequences, which will severely influence the whole supply chain. Thus, they have to be either forbidden or reduced to an acceptable risk level. The risk matrix method and the associated risk classifications are employed in a combined way in this work, as illustrated in Figure 3.3.



Likelihood Index (LI)		**Severity Index (SI)**			
		1 Minor	2 Moderate	3 Severe	4 Catastrophic
7	Very Frequent	7	8	9	10
6	Frequent	6	7	8	9
5	Likely	5	6	7	8
4	Possible	4	5	6	7
3	Unlikely	3	4	5	6
2	Rare	2	3	4	5
1	Extremely Rare	1	2	3	4

Figure 3.3. Category of risk levels in the risk matrix

Source: Developed by authors based on Wang and Foinikis (2001)

3.3.3.3 Validity and Reliability Test

A validity test aims to examine whether the study measures what it purports to measure, which normally can be improved by, for example, conducting an exhaustive literature review, incorporating expert opinions, and modifying the questionnaire according to the results of pilot test survey (Davis, 2000). Reliability refers to the consistency and stability of the results obtained. It is important to the validity of a questionnaire, but not a sufficient condition. The reliability test of the collected data can be carried out by using Cronbach's Alpha method with Eq. 3.6 (Cohen and Swerdlik, 2010).

$$\alpha = \frac{K}{K-1}\left(1-\frac{\sum_{i=1}^{K}\sigma_{Y_i}^2}{\sigma_X^2}\right) \qquad \text{Eq. 3.6}$$

Where, the K indicates the number of questions in the survey, σ_X^2 means the variance of the total sample, $\sigma_{Y_i}^2$ is the variance of the current question, and i represents the i^{th} question. Examination of the Cronbach's Alpha Based on Standardised Items can be achieved by Eq. 3.7.

$$\alpha_{standardised} = \frac{K\bar{\gamma}}{(1+(K-1)\bar{\gamma})} \qquad \text{Eq. 3.7}$$

Where, $\bar{\gamma}$ indicates the mean of the non-redundant correlation coefficients.

3.4 Risk Factor Classification and Identification

3.4.1 Framework for Risk Classification in Maritime Container Supply Chains

Based on a systematic review of the previous studies (e.g., Shashank and Goldsby, 2009; Acciaro and Serra, 2013; Ho et al., 2015; Zhao et al., 2016) and an in-depth discussion with domain experts through the Delphi survey, the framework for risk factors classification is proposed, as shown in Figure 3.4. It is a top-down structure framework, which helps to clarify the relationships among different risk sources step by step. It provides the basis for the identification of risk factors. It is composed of four levels (Level I, II, III, and IV). Level I, as the starting point, presents the purpose of this study, that is, to classify risk factors within MCSCs rationally. Level II divides all possible risk factors into two general categories, which are external risks and internal risks. The external risks usually result from an interaction between a supply chain and its environment, while internal risks arise due to improper coordination among different levels within a supply chain. In the next level, five main risk perspectives are identified from external and internal environments respectively, which are society, natural environment, management, infrastructure and technology, and operations. However, society offers a relatively broad concept comprising of a variety of human-related activities which may not be enough to support a specific risk factor identification. In view of this, society is further subdivided as economic environment (Heckmann et al., 2015), political environment (Yang, 2011), and security (Yang, 2010). Similarly, management and operations are also expanded, making up Level III. Such new developments in MCSC risk classification are supported by the Delphi expert group. Finally, 64 risk factors in Level IV are identified with respect to the risk perspectives (which will be discussed group by group in detail in Section 3.4.2) based on all risk sources identified from the upper level.

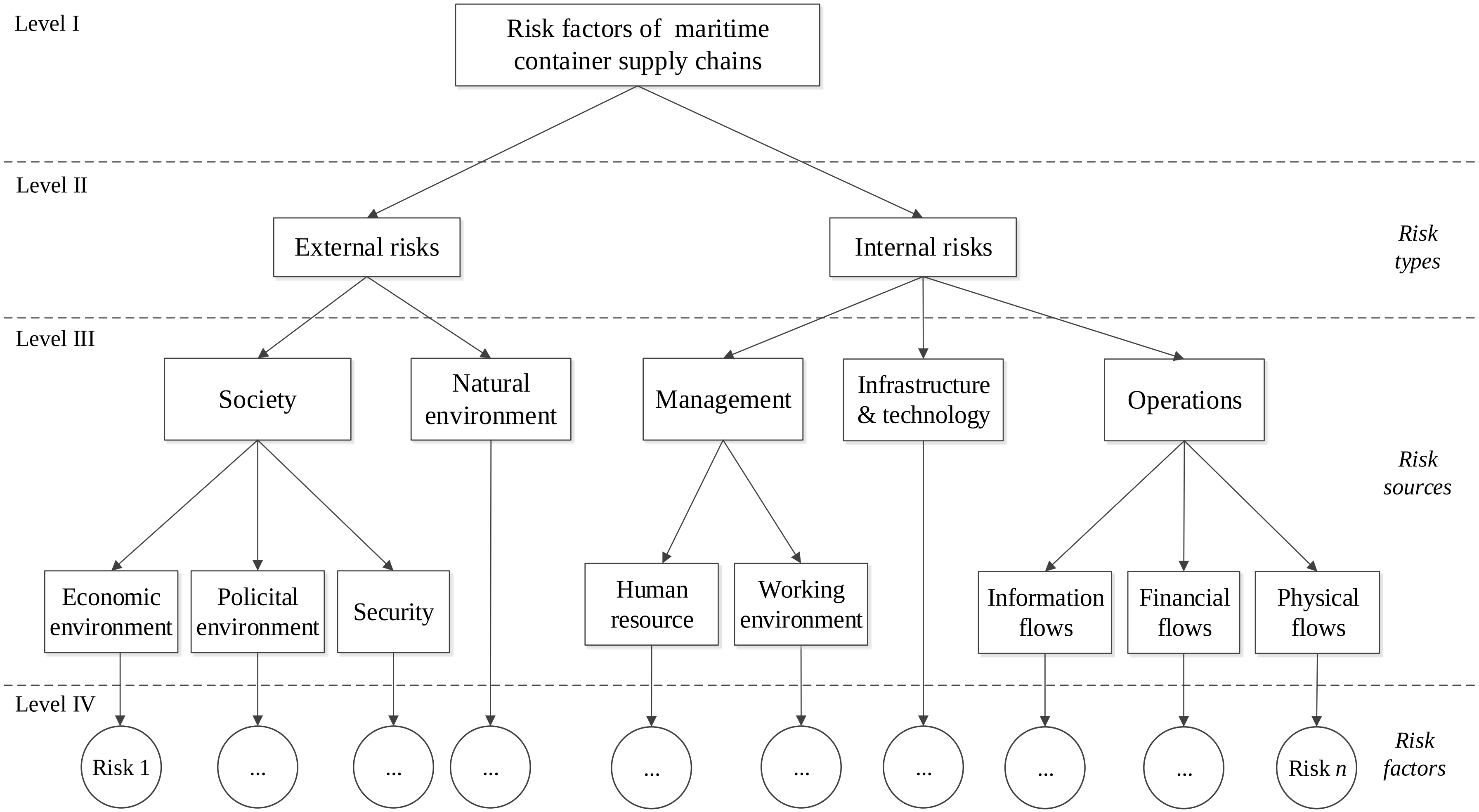


Figure 3.4. Framework for risk classification in MCSCs

3.4.2 Identification of Risk Factors in Maritime Container Supply Chains

Based on the framework proposed in the last section, the identification of risk factors in MCSCs was achieved through two main steps in this thesis. Firstly, a systematic review of relevant literature on risks associated with the MCSC processes was conducted to provide critical insights into the investigated risk factors in previous studies. In order to make the risk identification comprehensively, apart from the existing studies on risks in container shipping, the risks in a general supply chain were also included to be the background of risk identification. After that, a Delphi expert survey was conducted (as described in Section 3.3.1) to facilitate proper and comprehensive risk factor identification from industry practice. With the assistance of experience and knowledge from domain experts, all the risk factors identified in the literature review were confirmed. In addition, a number of risk factors that have not been addressed in previous studies were suggested by them. All the identified risk factors are discussed according to the sources in the following subsections.

3.4.2.1 Risk Factors Associated with Society

In this thesis, society belongs to a kind of external environment an MCSC relies on, where human activities are usually involved. In general, it can be divided into three categories, which are economic environment, political environment, and security. Each of them influences the performance and safety of MCSCs in different aspects.

The economic environment consists of factors in a business market that can influence a container shipping business directly or indirectly. Some factors may affect the business decision making on the part of the participants, such as turbulent shipping markets, and competition (Notteboom, 2004; Vilko et al., 2016). While, some will affect an entire economy and all of the participants invloved in an MCSC, such as the financial crisis, interest rates, and exchange rates (Vilko and Hallikas, 2012; Samvedi, Jain and Chan, 2013; Chang, Xu and Song, 2015). These factors will affect the price and investment, which increase the uncertainties in MCSC operations. Oil price is also an important risk factor to be considered, as bunker fuel makes up more than 75 per cent of the operating cost (Chang, Xu and Song, 2015).

The political environment is a critical concern for global trade, as government actions will inevitably affect the operations of a company or business on different levels. In this category, four main risk factors are identified, which are trade policy instability, maritime security initiatives, regulations and measures, and regional political conflicts (Tummala and Schoenherr, 2011; Vilko and Hallikas, 2012; Samvedi, Jain and Chan, 2013; Vilko et al., 2016).

Security mainly refers to the potential threats to MCSCs, which may result from malicious acts or other unpredictable events. Security risks not only worry supply chain managers, but also bring trouble to the public. Terrorism is one of the factors that has been studied by most of the researchers, especially after the 9/11 event. Piracy is also an important risk factor that is attracting attention from both industry and academia. Other relevant risk factors include sabotage, smuggling, spying/espionage, and epidemics (Manuj and Mentzer, 2008; Vilko and Hallikas, 2012; Acciaro and Serra, 2013; Chang, Xu and Song, 2015; Zhao, Yan and Zhang, 2016). It should be noted that the refugee immigrant is a factor that has been less investigated in previous studies, but it is recognised as a risk factor by some industry experts due to the increasing number of refugee immigrants in European countries in recent years. A summary of the above-identified risk factors can be found in Table 3.4.

Table 3.4. Risk factors associated with society

Risk sources		Risk factors	References
Society	Economic environment	Financial crisis	Vilko and Hallikas (2012); Chang, Xu and Song (2015)
		Change of interest rates	Manuj and Mentzer (2008); Samvedi, Jain, and Chan (2013)
		Change of exchange rates	Tummala and Schoenherr (2011); Samvedi, Jain, and Chan (2013); Chang, Xu, and Song (2015)
		Fluctuation of fuel price	Cucchiella and Gastaldi (2006); Manuj and Mentzer (2008)
		Unattractive markets	Vilko and Hallikas (2012)
		Fierce competition	Vilko and Hallikas (2012); Samvedi, Jain, and Chan (2013)
		Monopoly	Vilko et al. (2016)
	Political environment	Trade policy instability	Tummala and Schoenherr (2011); Samvedi, Jain, and Chan (2013); Vilko et al. (2016)
		Maritime security initiatives	Yang (2010); Acciaro and Serra (2013)
		Regulations and measures	Vilko and Hallikas (2012)
		Regional political conflicts	Vilko et al. (2016)
	Security	Terrorism	Tummala and Schoenherr (2011); Vilko and Hallikas (2012); Acciaro and Serra (2013); Chang, Xu and Song (2015); Vilko et al. (2016)
		Piracy/maritime robbery	Vilko and Hallikas (2012); Acciaro and Serra (2013); Chang, Xu, and Song (2015)
		Sabotage	Manuj and Mentzer (2008)
		Smuggling	Vilko and Hallikas (2012);

			Zhao, Yan and Zhang (2016)
		Spying/espionage	Vilko and Hallikas (2012)
		Epidemic	Vilko and Hallikas (2012); Vilko et al. (2016)
		Refugee immigrants	Identified from the expert survey

3.4.2.2 Risk Factors Associated with Natural Environment

It is another major component contributing to the external environment with a focus on the natural phenomena that could impair MCSC operations in the affected areas. The Changeable weather conditions are the one that has been experienced by most of the maritime container transportation. The complex navigation environment such as changeable weather, sea current, and wave, will impair the stability and safety of container ships, thus causing potential dangers to both cargos and seafarers. As the Earth’s weather is becoming more active, an increase in risks and catastrophic losses has been observed in maritime transport in recent years resulting from the natural hazards such as typhoons, storms, and other extreme weather events (Lam and Lassa, 2017). Meanwhile, global climate change has also emerged as a rising issue in the recent year, and its potential impact on the maritime transportation has been studied as early as in 2012 (Benamara and Asariotis, 2012). All the above-identified risk factors are summarised in Table 3.5.

Table 3.5. Risk factors associated with the natural environment

Risk sources	Risk factors	References
Natural environment	Changeable weather conditions	Notteboom (2006); Vilko and Hallikas (2012); Chang, Xu and Song (2015); Vilko et al. (2016)
	Natural hazards	Vilko and Hallikas (2012); Samvedi, Jain and Chan (2013); Ho et al. (2015)
	Climate change	Vilko and Hallikas (2012)

3.4.2.3 Risk Factors Associated with Management

Management in the proposed framework consists of two major parts, i.e. human resource and working environment. The former is primarily concerned with the management of people within organisations, such as the number, structure, quality, health (both physical and mental health), and wages of employees, while the latter involves not only the physical condition of the working environment including equipment, location, and surroundings, but also the atmosphere such as the culture of safety and teamwork within an enterprise. Among all risk factors, human error, which is claimed to be the main cause of maritime accidents according to the UK Marine Accident Investigation Branch (MAIB), should not be ignored. Another potential risk factor arising from the expert survey is ergonomics. Ergonomics aims to match the user with equipment and environment so as to optimise the overall system performance. It is especially important for those who work on board. Table 3.6 summarises the risk factors associated with management in an MCSC.

Table 3.6. Risk factors associated with the management

Risk sources		Risk factors	References
Management	Human resource	Lack of skilled workers	Vilko and Hallikas (2012); Mateusz and Świeboda (2014); Vilko et al. (2016)
		Lack of motivation	Vilko and Hallikas (2012); Vilko et al. (2016)
		Mental health of seafarers	Hetherington, Flin and Mearns, (2006); Mateusz and Świeboda (2014)
		Human errors	Hetherington, Flin and Mearns, (2006); expert survey
		Unreasonable salary and welfare	Identified from the expert survey
	Working environment	Language and cultural diversity	Hetherington et al. (2006);
		Lack of cooperation among departments	Yang et al. (2008)
		Poor safety culture/climate	Lu and Shang (2005); Hetherington et al. (2006)
		Low degree of safety leadership	Lu and Yang (2010)
		Poor ergonomics at the workplace	Identified from the expert survey

3.4.2.4 Risk Factors Associated with Infrastructure and Technology

Infrastructure and technology are the backbones supporting the sustainable development of a supply chain, as well as its operations in a reliable and efficient way. As a crucial node connecting different transportation modes of containers, lack of intermodal equipment will reduce the cargo handling capacity in terms of containers loading/unloading, and short-term transportation, and thus increase the waiting time of ships at ports. Other elements such as storage ability, berthing capability, entrance channels of a port, and ground access systems are also important to maximise port productivity. Regular maintenance helps to ensure the equipment (whether port machinery or equipment on board) runs efficiently. It is important to increase equipment's service life so that the total cost of investment during a life cycle can be reduced. Technical reliability indicates how much a technique fits the daily operations, and how long the applications of this technique can maintain a safe condition. The risk factors associated with infrastructure and technology are summarised in Table 3.7.

Table 3.7. Risk factors associated with infrastructure and technology

Risk sources	Risk factors	References
Infrastructure & technology	Lack of intermodal equipment	Vilko and Hallikas (2012)
	Poor entrance channels of a port	Vilko and Hallikas (2012); Vilko et al. (2016)
	Limited storage ability	Yang et al. (2008)
	Low technical reliability	Ho et al. (2015)
	Undeveloped ground access system of a port	Hsieh, Tai and Lee (2014)
	Lack of regular maintenance of equipment	Identified from the expert survey
	Insufficient berthing capability	Identified from the expert survey

3.4.2.5 Risk Factors Associated with Operations

Regarding the operations of maritime container logistics, three main flows which have been widely studied are information flows, financial flows, and physical flows (Chopra and Meindl, 2010).

Information flow mainly includes the transfer of data, knowledge or documents among different partners in a supply chain. The process of a supply chain relies heavily on information flows in terms of the product or service life cycle. Information flow can promote value-added activities and enhance the operational efficiency of supply chains. The speed and accuracy are two fundamental and key factors in existing methods of information transfer such as telephones calls, face-to-face meetings, emails, and Electronic Data Interchange (EDI), which may increase time in information transmission due to the usage of different information formats. Moreover, the effects of delay and inaccuracy may be amplified in a global supply chain network with more participants being involved. The lack of information standardisation and compatibility, as well as poor information sharing, will also reduce the quality and value of information, and thus lead to improper decision-making. During the Delphi survey, some experts also pointed out that “hide cargo information” can be a risk factor in terms of the information inaccuracy, although it may be different for the above reasons if considering how the inaccuracy is caused. IT vulnerability contains both hardware issues such as IT infrastructure breakdown and crash, and software issues including system failure, and other technical problems. With the rapid development of e-business in recent years, the wide usage of the internet also brings risks to information safety such as intrusion and fraud.

Financial flow refers to the economic-related activities in a supply chain, such as the payment for either goods or services, cash in and cash out of an enterprise, business cooperation with other partners within a supply chain, etc. Although there is no specific literature on risks associated with financial flow in container shipping, several related risk factors in the general supply chain context have been identified in previous studies. Tummala and Schoenherr (2011) stated that unrealised contracts with partners might lead to payment delay, and bankruptcy or having partners with bad credit may lead to non-payment. However, one expert from the Delphi survey pointed out that the impact of shippers going into bankruptcy may vary due to different international contracts of sale used in the container shipping business. According to the Delphi expert survey, ship charter rates also matter in terms of cost control. But, it is difficult to predict the trend of ship charter rates during the period of a contract, thus leading to uncertainties. Another risk factor that should be considered is cash flow, which is essential to keep a business afloat. Unfortunately, it is not rare in practice, and the problem is particularly prominent for small business owners.

The physical flow refers to the movement of container cargos in an MCSC, and it is perhaps the most important section during the whole process of container logistics as a type of transportation industry. From the perspective of a container shipping network, activities related to both port operations and maritime transportation of containers are taken into consideration in this thesis. Forecasting is the basis for supply chain members to make suitable plans of all kind of operational activities. However, it is not easy to capture changes arising from market or downstream members in order to make accurate forecasts, and the “bullwhip effect” in supply chain makes it even harder (Samvedi, Jain and Chan, 2012), thus damaging the competitiveness of a supply chain. This is also related to the management of containers, which will partly result in either the container shortage or transport of empty containers (in which trade imbalance on container shipping routes is another important contributor). In terms of the port operations, risk factors of port strikes, port/ terminal congestion, problems with customs clearance, improper container terminal operations, and improper management of container storage areas are identified (Notteboom, 2006; Tummala and Schoenherr, 2011; Chang, Xu and Song, 2015). While, risk factors of transportation of dangerous goods, lack of flexibility of designed schedules, electricity failure, bottlenecks/ restriction in the transportation routes, incorrect container packing, and transport accidents (such as ship contract, grounding, sinking, collision on quay, and oil spill) are considered with respect to the maritime transportation process (Vilko and Hallikas, 2012; Chang, Xu and Song 2015; Ho et al., 2015; Vilko et al., 2016). Among them, electricity failure is recognised to be an extremely severe risk factor in cold chain transportation, and transportation of dangerous goods is regarded as a special risk factor in the transportation industry supply chains compared to other general supply chains because explosions may cause huge damage to cargos, ships and even the nearby ports. For a container ship, the weight and centre of gravity of the hull itself are usually fixed, which however will change significantly after loading the cargo. The proper packing of cargos helps to maintain the stability of a ship during its sailing in the sea, thus having a greater impact on the safety of shipping. This risk factor contributed to more than half of the damaged cargo in 2017. Risk factors identified from the three main flows in MCSCs are summarised in Table 3.8.

Table 3.8. Risk factors associated with operations

Risk sources		Risk factors	References
Operations	Information flows	Information delay	Cucchiella and Gastaldi (2006); Vilko and Hallikas (2012); Chang, Xu and Song (2015)
		Information inaccuracy	Tummala and Schoenherr (2011); Chang, Xu and Song (2015)
		IT vulnerability	Tummala and Schoenherr (2011); Chang, Xu and Song (2015); Vilko et al. (2016)
		Internet security	Wu, Blackhurst and Chidambaram (2006)
		Poor information sharing	Vilko et al. (2016)
		Lack of information standardisation and compatibility	Tummala and Schoenherr (2011); Chang, Xu and Song (2015)
	Financial flows	Payment delay from partners	Seyoum (2014); Chang, Xu and Song (2015)
		Break a contract	Chang, Xu and Song (2015)
		Shippers going into bankruptcy	Tummala and Schoenherr (2011); Chang, Xu, and Song (2015)
		Partners with bad credit	Vilko and Hallikas (2012); Chang, Xu, and Song (2015)
		Charter rates rise	Identified from the expert survey
		Cash flow problem	Identified from the expert survey
	Physical flows	Inaccurate demand forecast	Manuj and Mentzer (2008); Samvedi, Jain, and Chan (2013); Ho et al. (2015)
		Transportation of dangerous goods	Vilko and Hallikas (2012); Chang, Xu, and Song (2015)
		Container shortage	Chang, Xu, and Song (2015)
		Port strikes	Notteboom (2006); Tummala and Schoenherr (2011); Chang, Xu, and Song (2015)
		Port/ terminal congestions	Notteboom (2006); Tummala and Schoenherr (2011); Chang, Xu, and Song (2015)
		Lack of flexibility of designed schedules	Tang and Nurmaya Musa (2011); Chang, Xu, and Song (2015); Ho et al. (2015); Vilko et al. (2016)

		Problems with customs clearance	Tummala and Schoenherr (2011); Vilko and Hallikas (2012); Chang, Xu, and Song (2015)
		Electricity failure	Chang, Xu, and Song (2015); Vilko et al. (2016)
		Bottlenecks/ restriction on transportation routes	Notteboom (2006); Vilko and Hallikas (2012); Vilko et al. (2016)
		Improper container terminal operations	Moon and Nguyen (2014)
		Incorrect container packing	Mateusz and Świeboda (2014); Chang, Xu, and Song (2015)
		Transport accidents	Yang et al. (2005); Ellis (2011); Vilko and Hallikas (2012)
		Trade imbalance on container shipping routes	Identified from the expert survey
		Improper management of container storage area	Identified from the expert survey

3.5 Screening of Risk Factors in MCSCs

A statistic of global trade shows that in 2016, China was ranked the first in terms of the merchandise exports and ranked the second in terms of merchandise imports. According to another recent statistics report (WSC, 2017b), among the top ten world's busiest container ports by the total number of actual twenty-foot equivalent units (TEUs) transported through the port, seven of them are in China. Given the fact[3], the data is collected from the maritime stakeholders in China, including the COSCO SHIPPING Lines Co., Ltd and its branches (such as COSCO Beijing International Freight Co., Ltd., COSCO Tianjin Shipping Agency Co., Ltd., COSCO shipping Logistics Co., Ltd., and COSCO SHIPPING Development Co., Ltd.), local maritime safety administrations (such as Changjiang Maritime Safety Administration), and major container ports in China (such as the Port of Shanghai), it is believed that the findings are meaningful in the region and can also be representative and provide insights for other regions given the involved fleets and ports in China are world leading, involving global MCSCs.

Table 3.9. Top three countries by imports and exports in 2016

Rank	Importers	USD (millions)	Exporters	USD (millions)
1	Unites States	2,248,209	China	2,097,637
2	China	1,587,921	Unites States	1,450,457
3	Germany	1,060,672	Germany	1,340,752

Source: International trade statistics (http://www.intracen.org/itc/market-info-tools/trade-statistics/)

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[3] It is also to improve the efficiency of data collection and address language barriers in the questionnaire design, timeliness of this research, and consensus issues of the primary data.

To systematically identify and analyse the risk factors in MCSCs, several methods are utilised in this chapter in a combined way. A Delphi expert survey is conducted to develop a risk classification framework, to validate the risk factors identified from the literature review, and to explore the emerging ones, which are not available from the current literature. A large-scale questionnaire survey is conducted to collect data for measuring the occurrence likelihood and consequence severity of each identified and validated risk factor. Finally, the risk matrix method is applied to analyse the relative importance of each risk factor.

3.5.1 Respondents' Profile in the Risk-Factor Survey

In this section, domain experts in container maritime logistics from 44 organisations (such as shipping companies, maritime safety administrations, customs, port authorities, and maritime university, etc.) are contacted using the university membership directories on maritime container logistics in Liverpool John Moores University, and Wuhan University of Technology. Also, domain experts with knowledge on risk management of any parts of the process of MCSCs had been contacted to elicit their opinions.

In total, 267 questionnaires were sent out in April 2017, and 101 replies were received by 13 June 2017. There were 71 valid questionnaires and 30 invalid ones (containing incomplete or conflicting information). The overall valid return rate is 26.59% (with a valid return rate of 64.10% for in-person distribution, and that of 20.18% for email distribution). To ensure the involvement of more validated experts, the questionnaire was also converted to an online edition via an e-survey creator. The website link to the online questionnaire was distributed to all potential participants (including those who did not reply to the email questionnaires) through instant messaging apps for the ease of finishing the questionnaire. The contacted researchers could sign in the e-survey creator and view the given answers when they completed it. 61 more valid replies were received by the end of June 2017. As a result, in total 132 valid responses were collected from the questionnaire survey. These data are firstly used to provide statistics of the likelihood and the consequence of each risk factor and then used to compute their *ARI*s. The summary of the questionnaire replies detail is shown in Table 3.10.

Table 3.10. A summary of questionnaire replies detail

	Questionnaire distributed	Questionnaire returned	Invalid replies	Valid replies	Valid reply rate
In-person	39	37	12	25	64.10%
By email	228	64	18	46	20.18%
Online	-	63	2	61	-

More than 75% of the respondents have worked in the container shipping industry for more than 10 years (11-15 years: 12.12%; 16-20 years: 35.61%; over 20 years: 28.79%), and meanwhile, more than 90% of respondents hold a middle-class job title or above, which reveals that the majority of the respondents have long professional working experience and abundant knowledge reserves in the container shipping business, contributing to the reliability of the results of this questionnaire survey.

In this survey, “academia” refers to researchers who work in, for example, maritime universities and research institutes with experience in conducting research projects on container shipping safety related issues. Most of the respondents from industry work in container shipping companies, while the rest work in companies including container shipping agencies, freight forwarding companies, and container terminals, which play important roles in maritime container logistics. Governmental bodies in this study represent maritime transportation authorities, including maritime safety administrations, shipping administrations, and port authorities. The category of “other” includes non-governmental organisations (NGO) in relation to the shipping industry such as China Logistics Association (CLA), and China Ship-owners’ Association (CSA). As an empirical study, respondents from industry (80.30%) hold a dominant position. The others, however, which account for nearly one-fifth of the total respondents (academia: 5.30%; governmental body: 12.12%; other: 2.27%), also provide a complementary view on the overall understanding of the whole MCSC from different perspectives. Among all the respondents, 8.33% and 31.82% of them take part in port operations and maritime transportation, respectively. The rest of them (59.85%) are involved in the whole process of MCSCs.

In terms of the size of the participating organisations, only 15.91% of the respondents work in small companies/organisations (fewer than 50 employees). More than 60% of the respondents work for companies/organisations with more than 200 employees, as the target sample is mainly selected from super-giant enterprises in the maritime shipping industry of their branches or agencies worldwide. The profile of 132 respondents in the survey is presented in Table 3.11.

Table 3.11. A summary of respondents’ profile

Respondent Profile		Number	%
What is the type of your organisation?	Academia	7	5.30%
	Industry	106	80.30%
	Governmental body	16	12.12%
	Other	3	2.27%

Which part of the process of a maritime container supply chain are you involved in?	Port operations	11	8.33%
	Maritime transportation	42	31.82%
	Whole process	79	59.85%
What is your job title/ position?	Primary (technical) job title[4]	10	7.58%
	Middle (technical) job title[5]	44	33.33%
	Advanced/Senior (technical) job title[6]	78	59.09%
For how many years have you worked in the container shipping or related industry?	1-5 years	12	9.09%
	6-10 years	19	14.39%
	11-15 years	16	12.12%
	16-20 years	47	35.61%
	Over 20 years	38	28.79%
How many employees are in your company/ organisation?	1-50 people	21	15.91%
	51-100 people	17	12.88%
	101-200 people	6	4.55%
	201-500 people	36	27.27%
	Over 500 people	52	39.39%

3.5.2 Validity and Reliability Test for Risk-Factor Survey

The validity and reliability of the results obtained from the questionnaire survey are of high concern to questionnaire builders, as they are the basis of obtaining a reasonable and convincing result in the follow-up analysis.

The questions of the risk-factor survey are developed from previous studies conducted in container shipping and general supply chain management, and have been validated through a Delphi expert survey from domain experts with rich experience in different aspects of maritime container shipping. Moreover, a pilot test was carried out to improve the questionnaire on both questions and response options before its distribution to a large scale. Besides, most of the respondents in the survey come from famous container shipping companies with professional working experience and knowledge in the field of container shipping. Therefore, this survey is believed to have a high level of validity.

The reliability of the questionnaire survey is measured using Cronbach's alpha method, as described in Section 3.3.3. A total of 124 questions were tested, including occurrence likelihood (64 questions), and risk consequence (64 questions). The results of reliability tests for the whole survey, the questions of likelihood, and questions of consequence are presented

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[4] Such as research assistant, assistant lecturer, assistant customs supervisor, and clerk.
[5] Such as research associate, lecturer, engineer, customs supervisor, and captain.
[6] Such as professor, senior engineer and above, senior customs supervisor, senior captain, and manager.

in Table 3.12. The Cronbach's alpha of the whole survey is 0.955 and Cronbach's Alpha Based on Standardised Items is 0.956. According to the criteria by Cohen and Swerdlik (2010), the result is acceptable when it is between 0.7 and 0.8, and the collected data is reliable when it is over 0.8. Therefore, this survey achieves a high level of reliability.

Table 3.12. Reliability test for the questionnaire survey

	Cronbach’s Alpha	Cronbach's Alpha Based on Standardised Items	Number of questions
Whole survey	0.955	0.956	128
Occurrence likelihood	0.930	0.932	64
Consequence severity	0.948	0.951	64

3.5.3 Analysis of Survey Results and Screening of Risk Factors

The results of the risk-factor questionnaire survey are firstly described from the aspects of risk likelihood and risk consequence, respectively. Then, the risk levels of each risk factor are analysed and presented using the risk matrix method, in order to identify the most significant ones.

3.5.3.1 Results in Relation to the Occurrence Likelihood of Risk Factors

Based on the risk matrix introduced in Section 3.3.2, occurrence likelihood is also divided into four levels in this thesis, which are 1) low level (in green colour), with a mean value of $LI \in [1, 2)$, 2) low- moderate level, which is represented in yellow colour with a mean value of $LI \in [2, 3.5)$, 3) high-moderate level, mapped in orange colour with a mean value of $LI \in [3.5, 5)$, and 4) high level (in red colour), with a mean value of $LI \in [5, 7]$. Although a seven-point scale has been used in the survey to measure the likelihood, no risk factor falls into scale 1, 6, and 7 after all respondents’ opinions are averaged, which means the occurrence likelihood of no risk factor is under low level (below scale 2).

Among the five main risk sources, risk factors associated with management have the highest likelihood (mean value: 4.25), which indicates that the human factor (and the working environment provided for daily operations) is a principal source bringing risks into container shipping industry in practice. It is followed by the likelihood of risk factors associated with operations (mean value: 3.99), and society (mean value: 3.79). Among all risk factors of all risk sources, the top ten risk factors in terms of likelihood are “fierce competition” (HS/EE_6: 5.58), “fluctuation of fuel price” (HS/EE_4: 5.13), “change of exchange rates” (HS/EE_3: 4.98), “trade imbalance on container shipping routes” (Op/PF_13: 4.86), “unattractive markets”

(HS/EE_5: 4.83), “port/ terminal congestions” (Op/PF_5: 4.59), “mental health of seafarers” (Man/HR _3: 4.55), “transportation of dangerous goods” (Op/PF_2: 4.53), “unreasonable salary and welfare” (Man/HR _5: 4.50), and “lack of motivation” (Man/HR _2: 4.42). These risk factors are mainly generated from human society, management, and operations. Moreover, the top three of them belong to economic environment risks under the category of human society, revealing the more often emerging uncertainties faced by entrepreneurs and managers in economic environment and activities.

In the category of economic environment, “fierce competition” and “fluctuation of fuel price” are two most likely happened risk factors, and also, they are the only two risk factors among all that fall into the high level of occurrence likelihood (with a mean value over 5). Another risk factor worth noting is “monopoly”. Although its occurrence likelihood is not outstanding (mean value: 4.02), its Standard Deviation (SD) is the greatest one among all identified risk factors. This indicates the deviations in the understanding and definition of monopoly among all respondents. The monopoly can be a problem according to some respondents (e.g. those from port/terminal operators and shipping companies), while other respondents (e.g. those from port authorities and universities) may care less about this problem. Table 3.13 summarises the data acquired from the questionnaire survey on the occurrence likelihood of all risk factors.

Table 3.13 Likelihood of risk factors

Risk factors associated with **society**		Mean	S.D.	Rank	
Economic Environment (EE)				L	G
1. Financial crisis	HS/EE_1	3.70	1.71	7	
2. Change of interest rates	HS/EE_2	4.38	1.34	5	
3. Change of exchange rates	HS/EE_3	4.98	1.30	3	3
4. Fluctuation of fuel price	HS/EE_4	5.13	1.34	2	2
5. Unattractive markets	HS/EE_5	4.83	1.38	4	5
6. Fierce competition	HS/EE_6	5.58	1.38	1	1
7. Monopoly	HS/EE_7	4.02	1.78	6	
Mean value of EE		4.66			
Political Environment (PE)					
1. Trade policy instability	HS/PE_1	3.50	1.26	4	
2. Maritime security initiatives	HS/PE_2	3.75	1.13	2	
3. Regulations and measures	HS/PE_3	3.83	1.42	1	
4. Regional political conflicts	HS/PE_4	3.52	1.54	3	
Mean value of PE		3.65			
Security (SE)					
1. Terrorism	HS/SE_1	2.56	1.36	7	
2. Piracy /maritime robbery	HS/SE_2	3.04	1.35	2	

3. Sabotage	HS/SE_3	2.63	1.13	6	
4. Smuggling	HS/SE_4	4.06	1.31	1	
5. Spying /espionage	HS/SE_5	2.94	1.61	4	
6. Epidemic	HS/SE_6	2.98	1.15	3	
7. Refugee immigrants	HS/SE_7	2.73	1.19	5	
Mean value of SE		2.99			
Mean value of risks associated with society		3.79			
Risk factors associated with **natural environment**					
1. Changeable weather conditions	NE_1	4.43	1.61	1	
2. Natural hazards	NE_2	2.92	1.19	3	
3. Climate change	NE_3	3.19	1.57	2	
Mean value of risks associated with natural environment		3.51			
Risk factors associated with **management**					
Human Resource (HR)					
1. Lack of skilled workers	Man/HR _1	4.15	1.15	5	
2. Lack of motivation	Man/HR _2	4.42	1.28	3	10
3. Mental health of seafarers	Man/HR _3	4.55	1.37	1	7
4. Human errors	Man/HR _4	4.37	1.09	4	
5. Unreasonable salary and welfare	Man/HR _5	4.50	1.44	2	9
Mean value of HR		4.40			
Working Environment (WE)					
1. Language and cultural diversity	Man/WE_1	4.08	1.55	3	
2. Lack of cooperation among departments	Man/WE_2	4.30	1.29	1	
3. Poor safety culture/climate	Man/WE_3	4.22	1.33	2	
4. Low degree of safety leadership	Man/WE_4	3.88	1.32	5	
5. Poor ergonomics at workplace	Man/WE_5	4.02	1.19	4	
Mean value of WE		4.10			
Mean value of risks associated with management		4.25			
Risk factors associated with **infrastructure and technology**					
1. Lack of intermodal equipment	I & T _1	3.45	1.21	6	
2. Poor entrance channels of a port	I & T _2	3.88	1.30	3	
3. Limited storage ability	I & T _3	3.33	1.18	7	
4. Low technical reliability	I & T _4	3.50	1.10	5	
5. Undeveloped ground access system of a port	I & T _5	3.53	1.15	4	
6. Lack of regular maintenance of equipment	I & T _6	3.94	1.09	2	
7. Insufficient berthing capability	I & T _7	4.07	1.14	1	
Mean value of risks associated with infrastructure and technology		3.67			
Risk factors associated with **operations**					
Information Flow (IF)					
1. Information delay	Op/IF_1	4.31	1.41	1	
2. Information inaccuracy	Op/IF_2	4.28	1.27	2	
3. IT vulnerability	Op/IF_3	3.81	1.31	4	
4. Internet security	Op/IF_4	3.70	1.45	5	
5. Poor information sharing	Op/IF_5	3.86	1.33	3	

6. Lack of information standardisation and compatibility	Op/IF_6	3.70	1.28	5	
Mean value of IF		3.95			
Financial Flow (FF)					
1. Payment delay from partners	Op/FF_1	4.25	1.21	1	
2. Break a contract	Op/FF_2	3.98	1.24	4	
3. Shippers going into bankruptcy	Op/FF_3	3.50	1.36	6	
4. Partners with bad credit	Op/FF_4	3.91	1.33	5	
5. Charter rates rise	Op/FF_5	4.14	1.18	2	
6. Cash flow problem	Op/FF_6	4.04	1.43	3	
Mean value of FF		3.97			
Physical Flow (PF)					
1. Inaccurate demand forecast	Op/PF_1	4.36	1.24	4	
2. Transportation of dangerous goods	Op/PF_2	4.53	1.44	3	8
3. Container shortage	Op/PF_3	3.88	1.33	9	
4. Port strikes	Op/PF_4	3.34	1.17	14	
5. Port/ terminal congestions	Op/PF_5	4.59	1.37	2	6
6. Lack of flexibility of designed schedules	Op/PF_6	4.02	1.23	6	
7. Problems with customs clearance	Op/PF_7	3.91	1.29	8	
8. Electricity failure	Op/PF_8	3.59	1.11	13	
9. Bottlenecks/restriction on transportation routes	Op/PF_9	3.66	1.29	12	
10. Improper container terminal operations	Op/PF_10	4.03	1.32	5	
11. Incorrect container packing	Op/PF_11	3.69	1.33	10	
12. Transport accidents	Op/PF_12	3.67	1.21	11	
13. Trade imbalance on container shipping routes	Op/PF_13	4.86	1.32	1	4
14. Improper management of container storage area	Op/PF_14	4.00	1.11	7	
Mean value of PF		4.01			
Mean value of risks associated with operations		3.99			

S.D. = Standard Deviation
Rank L means the local rank of each risk factor under its category (main risk source).
Rank G means the global rank of each risk factor among all (only the top 10 are shown.)

3.5.3.2 Results in Relation to the Consequence Severity of Risk Factors

Four levels of consequence in this thesis are 1) low level, in green colour, with a mean value of $SI \in [1, 2)$, 2) low-moderate level, in yellow colour, with a mean value of $SI \in [2, 2.5)$, 3) high-moderate level, in orange colour, with a mean value of $SI \in [2.5, 3)$, and 4) high level, in red colour, with a mean value of $SI \in [3, 4]$. It can be seen from the consequence severity of all identified risk factors that the majority of the risk factors fall into the scale between 2 and 3.

Among all risk sources, risk factors associated with human society are identified to have the greatest influence in terms of consequence severity, with a mean value of 2.31. As an important component of the external environment, it is crucial for managers to pay attention to the related risk factors in order to reduce their negative impacts on the operation of a business. The category of risk factors associated with operations (mean value: 2.30) ranks second, and that associated with management (mean value: 2.25) is in the third place.

Among all the identified risk factors, the top ten in terms of consequence severity are "terrorism" (HS/SE_1: 3.23), "piracy /maritime robbery" (HS/SE_2: 3.08), "financial crisis" (HS/EE_1: 3.02), "regional political conflicts" (HS/PE_4: 2.95), "shippers going into bankruptcy" (Op/FF_3: 2.77), "transportation of dangerous goods" (Op/PF_2: 2.72), "transport accidents" (Op/PF_12: 2.69), "natural hazards" (NE_2: 2.59), "Low degree of safety leadership" (Man/WE_4: 2.53), "break a contract" (Op/FF_2: 2.53), "port strikes" (Op/PF_4: 2.53), and "change of exchange rates" (HS/EE_3: 2.52). It should be noted that risk factors Man/WE_4, Op/FF_2, and Op/PF_4 hold the same mean value of 2.53, ranking the 9th place at the same time, and that is the reason why altogether twelve risk factors are mentioned here. Human society and the operations are identified as the main sources (7 out of 10) where these risk factors come from.

There are three risk factors which have been identified as high-level risks in terms of consequence severity, which are a financial crisis, terrorism, and piracy/maritime robbery. For example, the financial crisis in 2008 led to the economic downturn of many countries worldwide, and the container shipping industry has been seriously affected for a long time due to the fact that its development heavily depends on the prosperity of global trade. Security issues such as terrorism and piracy have been emphasised and received a lot of attention in both industry and academia in recent years. According to Ewence (2011), more than 7 billion dollars could be the cost per year to shipping companies and governments to deal with the Somalia piracy. Apart from the risk factors such as change of interest rates, maritime security initiatives, and refugee immigrants, which belong to low-level risks in terms of consequence severity, the rest fall into the moderate level. A summary of all the data on risk factors in terms of consequence severity is listed in Table 3.14.

Table 3.14. Estimated consequence severity of risk factors

Risk factors associated with **society**		Mean	S.D.	Rank	
Economic Environment (EE)				L	G
1. Financial crisis	HS/EE_1	3.02	0.68	1	3
2. Change of interest rates	HS/EE_2	1.86	0.77	7	
3. Change of exchange rates	HS/EE_3	2.52	0.73	2	10
4. Fluctuation of fuel price	HS/EE_4	2.47	0.59	3	

5. Unattractive markets	HS/EE_5	2.43	0.60	4	
6. Fierce competition	HS/EE_6	2.41	0.77	5	
7. Monopoly	HS/EE_7	2.38	0.83	6	
Mean value of EE		2.44			
Political Environment (PE)					
1. Trade policy instability	HS/PE_1	2.25	0.64	2	
2. Maritime security initiatives	HS/PE_2	1.92	0.74	4	
3. Regulations and measures	HS/PE_3	2.13	0.65	3	
4. Regional political conflicts	HS/PE_4	2.95	0.81	1	4
Mean value of PE		2.31			
Security (SE)					
1. Terrorism	HS/SE_1	3.23	1.12	1	1
2. Piracy /maritime robbery	HS/SE_2	3.08	1.09	2	2
3. Sabotage	HS/SE_3	2.38	1.00	3	
4. Smuggling	HS/SE_4	2.00	0.87	5	
5. Spying /espionage	HS/SE_5	1.94	0.83	6	
6. Epidemic	HS/SE_6	2.14	0.89	4	
7. Refugee immigrants	HS/SE_7	1.83	0.79	7	
Mean value of SE		2.37			
Mean value of risks associated with society		2.39			
Risk factors associated with **natural environment**					
1. Changeable weather conditions	NE_1	2.08	0.76	2	
2. Natural hazards	NE_2	2.59	1.00	1	8
3. Climate change	NE_3	1.80	0.74	3	
Mean value of risks associated with natural environment		2.16			
Risk factors associated with **management**					
Human Resource (HR)					
1. Lack of skilled workers	Man/HR _1	2.47	0.77	1	
2. Lack of motivation	Man/HR _2	2.14	0.75	4	
3. Mental health of seafarers	Man/HR _3	2.26	0.78	3	
4. Human errors	Man/HR _4	2.32	0.64	2	
5. Unreasonable salary and welfare	Man/HR _5	2.09	0.75	5	
Mean value of SE		2.26			
Working Environment (WE)					
1. Language and cultural diversity	Man/WE_1	1.80	0.76	5	
2. Lack of cooperation among departments	Man/WE_2	2.25	0.71	3	
3. Poor safety culture/climate	Man/WE_3	2.23	0.81	4	
4. Low degree of safety leadership	Man/WE_4	2.53	0.87	1	9
5. Poor ergonomics at workplace	Man/WE_5	2.41	0.77	2	
Mean value of WE		2.24			
Mean value of risks associated with management		2.25			
Risk factors associated with **infrastructure and technology**					
1. Lack of intermodal equipment	I & T _1	2.19	0.66	4	
2. Poor entrance channels of a port	I & T _2	2.33	0.71	2	
3. Limited storage ability	I & T _3	2.08	0.72	6	

4. Low technical reliability	I & T _4	2.22	0.70	3	
5. Undeveloped ground access system of a port	I & T _5	2.19	0.71	4	
6. Lack of regular maintenance of equipment	I & T _6	2.38	0.72	1	
7. Insufficient berthing capability	I & T _7	2.17	0.70	5	
Mean value of risks associated with infrastructure and technology		2.22			
Risk factors associated with **operations**					
Information Flow (IF)					
1. Information delay	Op/IF_1	2.06	0.73	4	
2. Information inaccuracy	Op/IF_2	2.36	0.76	2	
3. IT vulnerability	Op/IF_3	2.30	0.85	3	
4. Internet security	Op/IF_4	2.38	0.86	1	
5. Poor information sharing	Op/IF_5	1.94	0.66	5	
6. Lack of information standardisation and compatibility	Op/IF_6	2.06	0.66	4	
Mean value of IF		2.18			
Financial Flow (FF)					
1. Payment delay from partners	Op/FF_1	2.31	0.69	4	
2. Break a contract	Op/FF_2	2.53	0.69	2	9
3. Shippers going into bankruptcy	Op/FF_3	2.77	0.73	1	5
4. Partners with bad credit	Op/FF_4	2.27	0.74	5	
5. Charter rates rise	Op/FF_5	2.23	0.61	6	
6. Cash flow problem	Op/FF_6	2.50	0.83	3	
Mean value of FF		2.43			
Physical Flow (PF)					
1. Inaccurate demand forecast	Op/PF_1	2.22	0.68	8	
2. Transportation of dangerous goods	Op/PF_2	2.72	0.79	1	6
3. Container shortage	Op/PF_3	2.13	0.63	10	
4. Port strikes	Op/PF_4	2.53	0.80	3	9
5. Port/ terminal congestions	Op/PF_5	2.33	0.71	7	
6. Lack of flexibility of designed schedules	Op/PF_6	1.92	0.80	14	
7. Problems with customs clearance	Op/PF_7	2.02	0.77	13	
8. Electricity failure	Op/PF_8	2.39	0.81	5	
9. Bottlenecks/restriction on transportation routes	Op/PF_9	2.34	0.65	6	
10. Improper container terminal operations	Op/PF_10	2.20	0.74	9	
11. Incorrect container packing	Op/PF_11	2.42	0.92	4	
12. Transport accidents	Op/PF_12	2.69	0.85	2	7
13. Trade imbalance on container shipping routes	Op/PF_13	2.03	0.64	12	
14. Improper management of container storage area	Op/PF_14	2.09	0.73	11	
Mean value of PF		2.29			
Mean value of risks associated with operations		2.30			

S.D. = Standard Deviation

Rank L means the local rank of each risk factor under its category (risk source).

Rank G means the global rank of each risk factor among all (only the top 10 are shown.)

3.5.3.3 Risk Level Analysis of Risk Factors

Based on the statistics of occurrence likelihood and consequence severity from all respondents, *ARI*s for each risk factor can be calculated using Eq. 3, and then be grouped into different risk levels defined in Figure 3 (see Table 3.15). The top ten risk factors in terms of the values of ARI are “fierce competition” (HS/EE_6: 6.98), “fluctuation of fuel price” (HS/EE_4: 6.59), “change of exchange rates” (HS/EE_3: 6.50), “unattractive markets” (HS/EE_5: 6.26), “transportation of dangerous goods” (Op/PF_2: 6.25), “port/terminal congestions” (Op/PF_5: 5.92), “trade imbalance on container shipping routes” (Op/PF_13: 5.89), “mental health of seafarers” (Man/HR _3: 5.81), “financial crisis” (HS/EE_1: 5.72), and “human errors” (Man/HR _4: 5.69). Among them, the top five risk factors are located in the high-moderate level, while the rest belong to the low-moderate level. The macroeconomic environment plays a crucial role that can influence a container shipping business both directly and indirectly. Some factors partially affect the business decision making, including turbulent shipping markets, and competition (Notteboom, 2004; Vilko et al., 2016). Some will affect the entire economy and all of the participants, such as the financial crisis (Vilko and Hallikas, 2012; Samvedi et al., 2013; Chang, Xu and Song, 2015). These factors will affect the price and investment, which increases the uncertainties in MCSC operations. Transportation of dangerous good is regarded as a special risk factor in the container transportation compared to other general supply chains because accidents such as explosions, leakage of hazardous chemical materials, and fire during the transportation of dangerous good can cause huge damage to cargos, ships, and even the nearby ports. Port/terminal congestion will increase the waiting time of a ship in port areas, thus making it difficult to keep to the fixed schedule. Appropriate and effective management of empty containers caused by trade imbalance is also a major issue, which contributes to both financial savings and environment protection (Song and Carter, 2009). Due to the harsh working environment on board a ship, seafarers usually suffer from mental health problems such as fatigue, stress, and anxiety, which will negatively affect their behaviour and increase the risks at sea. Human error is recognised as one of the main causal factors in up to 80% of accidents across various industries (Stewart and Chase, 2010). It is interesting to note that although the terrorism and piracy are of great significance in terms of severity, they are only ranked at 51st (HS/SE_1: 4.79) and 36th (HS/SE_2: 5.12) in terms of *ARI* respectively when taking into account their relatively low frequency of occurrence. Although some of the factors were analysed in previous studies to have high risk levels, they were tackled only with reference to the limited investigated scope (often a segment of a chain) and thus have received relatively low *ARI*s in this systematic analysis within the context of the whole MCSCs. The facts that 1) there are few studies presenting and comparing the risk factors influencing container shipping chains as a whole, and 2) fewer providing quantitative risk index to reveal their safety prioritisation empirically, reveal the new findings and contributions of this work. The *ARI*s, as well as the risk levels of all identified risk factors, are summarised in Table 3.15.

Table 3.15. *ARI* values and risk level of all risk factors

Risk sources	Risk factors	ARI	Risk level
Human society *ARI*: 6.17	HS/EE_1	5.72	Low-moderate
	HS/EE_2	5.23	Low-moderate
	HS/EE_3	6.50	High-moderate
	HS/EE_4	6.59	High-moderate
	HS/EE_5	6.26	High-moderate
	HS/EE_6	6.98	High-moderate
	HS/EE_7	5.40	Low-moderate
	HS/PE_1	4.75	Low-moderate
	HS/PE_2	4.67	Low-moderate
	HS/PE_3	4.95	Low-moderate
	HS/PE_4	5.47	Low-moderate
	HS/SE_1	4.79	Low-moderate
	HS/SE_2	5.12	Low-moderate
	HS/SE_3	4.00	Low-moderate
	HS/SE_4	5.06	Low-moderate
	HS/SE_5	3.88	Low
	HS/SE_6	4.13	Low-moderate
	HS/SE_7	3.56	Low
Natural environment *ARI*: 5.67	NE_1	5.51	Low-moderate
	NE_2	4.52	Low-moderate
	NE_3	3.98	Low
Management *ARI*: 6.50	Man/HR _1	5.62	Low-moderate
	Man/HR _2	5.56	Low-moderate
	Man/HR _3	5.81	Low-moderate
	Man/HR _4	5.69	Low-moderate
	Man/HR _5	5.59	Low-moderate
	Man/WE_1	4.88	Low-moderate
	Man/WE_2	5.55	Low-moderate
	Man/WE_3	5.45	Low-moderate
	Man/WE_4	5.41	Low-moderate
	Man/WE_5	5.42	Low-moderate
Infrastructure & technology *ARI*: 5.89	I & T _1	4.64	Low-moderate
	I & T _2	5.20	Low-moderate
	I & T _3	4.41	Low-moderate
	I & T _4	4.72	Low-moderate

	I & T _5	4.72	Low-moderate
	I & T _6	5.32	Low-moderate
	I & T _7	5.24	Low-moderate
Operations *ARI*: 6.28	Op/IF_1	5.38	Low-moderate
	Op/IF_2	5.64	Low-moderate
	Op/IF_3	5.11	Low-moderate
	Op/IF_4	5.08	Low-moderate
	Op/IF_5	4.80	Low-moderate
	Op/IF_6	4.77	Low-moderate
	Op/FF_1	5.56	Low-moderate
	Op/FF_2	5.52	Low-moderate
	Op/FF_3	5.27	Low-moderate
	Op/FF_4	5.17	Low-moderate
	Op/FF_5	5.38	Low-moderate
	Op/FF_6	5.54	Low-moderate
	Op/PF_1	5.58	Low-moderate
	Op/PF_2	6.25	High-moderate
	Op/PF_3	5.00	Low-moderate
	Op/PF_4	4.88	Low-moderate
	Op/PF_5	5.92	Low-moderate
	Op/PF_6	4.94	Low-moderate
	Op/PF_7	4.92	Low-moderate
	Op/PF_8	4.98	Low-moderate
	Op/PF_9	5.00	Low-moderate
	Op/PF_10	5.23	Low-moderate
	Op/PF_11	5.11	Low-moderate
	Op/PF_12	5.36	Low-moderate
	Op/PF_13	5.89	Low-moderate
	Op/PF_14	5.09	Low-moderate

It is notable that almost all risk factors except for “Spying /espionage” (HS/SE_5:3.88), “Refugee immigrants” (HS/SE_7:3.56), and “Climate change” (NE_3:3.98), fall into the moderate risk level with an $ARI \in [4, 8)$, which is in harmony with the experience of domain experts. According to the survey results, the spying/espionage risk is recognised to be acceptable, which may be partly due to the fact that business espionage is not a common issue in the container shipping industry. The refugee immigrant is a factor that has been less investigated in previous studies, but it is recognised as a risk factor by more and more experts due to the increasing number of refugee immigrants in European countries in recent years. However, its impact on the container shipping industry has not been evidenced currently, compared to other high-risk factors. It is also probably due to the limitation of this study by having less response from the EU, which will be further addressed in future by conducting a global survey. Regarding the global climate change, which has been an emerging research topic in recent years, especially in the area of transportation resilience and port operations (e.g. Brown et al., 2012; Wan et al., 2017), although there is less direct evidence compared to other risk factors of a moderate risk in terms of negative effect, its risk index value (3.98) is the highest in non-moderate risk factors. It well reflects the observation from the survey in which experts are aware of and pay increasing attention to the impact of climate change to container transport logistics (particularly ports), however high uncertainty in terms of the frequency of climate disasters made them conservative when evaluating its likelihood. It looks likely that with more evidence collected from climate accidents (e.g. hurricanes in The Gulf of Mexico in 2016), the risk index of climate change within the context of MCSCs will increase in future.

3.6 Conclusion

Identification of risk factors provides the foundation for supply chain risk analysis and accident prevention. In this Chapter, a new risk factor classification framework is developed, including five main risk sources namely society, natural environment, management, infrastructure and technology, and operations. The first two are external risk sources, whereas the rest three belong to internal ones. It integrates different classification methods and incorporates them in a logical hierarchy suitable for modelling the risk factors influencing MCSCs. Its development is validated by a Delphi expert group of 10 persons through three-round verification process. Based on that, 64 risk factors are identified through a critical review of previous studies, along with an exploration and validation process using a Delphi expert survey. These risk factors are assessed from the aspects of occurrence likelihood and consequence severity by conducting a questionnaire survey, and they are further categorised into different risk levels and ranked according to their ARIs calculated through the risk matrix analysis. The results show that “fierce competition”, “fluctuation of fuel price”, “change of exchange rates”, “unattractive markets”, “transportation of dangerous goods”, “port/ terminal congestions”, “trade imbalance on container shipping routes”, “mental health of seafarers, “financial crisis”, and “human errors” are the top ten risk factors influencing the safe and effective operations of an MCSC.

Furthermore, the research results based on empirical data further not only prove the relevant findings from previous studies but also involve new contributions by providing quantitative risk prioritisation information. In Lam and Bai’s (2016) research, risks associated with the IT system, operational risks, and human resource management risk were identified as the top three risks. In our research, management (which is composed of the management of human resource and working environment) is the main risk source with an ARI of 5.50, while risk factors related to operations are ranked the second with an ARI of 5.28. In line with the research findings of Notteboom and Vernimmen (2009) and Chang, Xu and Song (2014), our research discloses that the fluctuation of fuel price (specifically, fuel price rise) is an important risk factor. It ranks the second of all risk factors with high likelihood and consequence. Thus it deserves the attention of carriers as bunker fuel accounts for more than three quarters of the operating cost (Ronen, 2011). Our research findings also emphasise that the transportation of dangerous goods is an important risk factor (Chang, Xu and Song, 2015). It ranks the first among operational risk factors, and ranks the fifth among all, belonging to a high-moderate risk level with an ARI of 6.25.

Although the risk matrix method provides a clear framework for systematic review of individual risk factors and convenient documentation for the rationale of risk rankings (Cox, 2008), it suffers from some mathematical limitations that should not be ignored such as weak consistency and ambiguous outputs (Cox, 2008). For specific, risk matrices show limited ability to correctly reproduce the risk ratings implied by quantitative models, especially for categorizing black swan events (i.e. the incidents that occur in a very low probability but with severe and wide-spread influence). Errors may occur when comparatively ranking risk factors under such situation. This suggests that risk matrices should be used with caution. In view of this, a novel risk assessment method will be proposed in the next chapter to further investigate the identified risk factor in order to provide a more comprehensive evaluation of the risk factors in MCSCs.

CHAPTER 4 - AN ADVANCED APPROACH FOR RISK ASSESSMENT OF MARITIME CONTAINER SUPPLY CHAINS

Summary

This chapter, as a follow-up study of Chapter 3, illustrates an efficient and powerful belief rule-based Bayesian network (BR-BN) method to deal with the in-depth assessment of identified risk factors and prioritise them under uncertain environment. The proposed method is mainly composed of two parts. The first one is the belief rule base (BRB) which is particularly established for evaluating the container maritime logistics risks in this study. A BRB is a collection of fuzzy rules with belief structure which are made up of an antecedent part and a consequent part. Then the relationships of attributes between the two parts are modelled in the Bayesian network (BN) so that all relevant rules can be aggregated for evaluating and prioritising risk factors. A case study of one Chinese container shipping company is conducted to illustrate the application of the proposed model.

4.1 Introduction

The research work in Chapter 3 mainly dealt with the identification and classification of risk factors in MCSCs, in which the risk factors identified were broadly classified into four different levels according to their ARIs with the careful usage of risk matrix analysis. It offers an effective and straightforward screening tool for managers to focus their attention on the initial phase of supply chain risk management (Cox, 2008). However, when an in-depth analysis of risk factors is required, the traditional risk analysis method introduced in Chapter 3 may not be able to provide sufficient safety management information.

In the past decade, numerous methods (either qualitative or quantitative) have been proposed in terms of their applications in the different stages of supply chain risk management, especially for risk identification and assessment. They are, for example, the analytic hierarchy process (AHP) method (Gaudenzi and Borghesi, 2006), TOPSIS method (Samvedi, Jain, and Chan, 2013), and the Failure Mode, Effect Analysis (FMEA) (Pujawan and Geraldin, 2009). These traditional risk analysis and decision making tools are popular due to their easiness and visibility when conducting quantitative risk evaluation. However, under many circumstances, they have shown inherent drawbacks and incapability of providing accurate and real-time risk estimate in their practical applications. The high uncertainty in risk data in container supply chains also constrains their application in risk analysis of MCSCs (Alyami, 2016). Thus, new models based on advanced uncertainty methods have been developed to overcome the deficiencies, including fuzzy logic, Dempster-Shafer theory, Bayesian Networks (BNs), and Monte Carlo simulation (Yang, Bonsall and Wang, 2008).

A review of 224 journal papers by Ho et al. (2015) revealed that most of the previous research on supply chain risk assessments paid special attention to the occurrence probability of an event. Few studies assessed the severity of the consequences, leaving the other features of risk not being fully explored. Although supply chain risks have already been assessed from the two aspects of likelihood and consequence, the existing studies have not addressed more risk parameters for advanced risk analysis of complicated supply chain systems. Therefore, it is necessary to understand better the risk management of MCSCs involving multimodal transport and develop flexible risk approaches capable of tackling uncertainties for precise risk assessment.

In light of this research need, an effective risk assessment tool should at least have the following two characteristics. First, the method should be able to process different types of information (e.g. quantitative and qualitative, subjective and objective) from multiple sources in a consistent manner. Second, the method should be able to provide accurate results while maintaining a certain degree of visibility, transparency, as well as easiness to operate. In this paper, we propose an advanced risk modelling approach by incorporating the fuzzy rule base (FRB) with BNs to evaluate and prioritise risk events in MCSCs. FRB is used to elicit expert judgments and to rationalize the configuration of subjective probabilities. The Bayesian marginalization rules are employed to accommodate all relevant IF-THEN rules with belief structures and to calculate risk priority values of all identified risk events. The novelty of this chapter is threefold. First, the study incorporates new risk parameters which can be used to better model risks of MCSCs. Second, it introduces a new method to rationalize the degrees of belief (DoB) distribution in fuzzy IF-THEN rules by taking the weight of each risk parameter into account when constructing the BRB. Third, it systemically identifies and analyses the risk events relating to MCSCs from multiple dimensions of operations, environmental and economic.

The rest of this chapter is organised as follows. In Section 4.2 detailed information of the selected risk parameters is discussed, along with the development and application of fuzzy rule bases. Section 4.3 elaborates the risk analysis and inference framework step by step. The application and validation of the method are carried out in Section 4.4 with a real case study. The calculation of the risk assessment results and the validation process are achieved by using a user-friendly software package, which enables the end users to collect raw data from the real observations and perform calculation easily. Finally, this chapter is concluded in Section 4.5.

4.2 Background information

4.2.1 Extensions of Risk Parameters in Maritime Supply Chains

As discussed in Section 2.3.1, such studies often argue that having two basic risk parameters (i.e. *P* and *C*) will sometimes lead to the loss of useful information in risk analysis. However, considering more risk parameters is not necessarily better. This is particularly true for industrial cases as more resources (e.g., data, time, and expert knowledge) are usually required to support an in-depth risk assessment, increasing risk management costs. It is, therefore, crucial to strike a good balance between the number of risk parameters/accuracy of risk analysis results and the cost of carrying out a risk estimate. In this study, two main extensions are considered to rationalise the risk assessment of MCSCs. The first one is the **visibility** of risk in a supply chain (Vilko, Ritala, and Hallikas, 2016), and the other is the decomposition of consequence into three categories, based on different types of impacts. They are **time delay/disruption**, **additional cost/financial loss**, and **quality damage** (Vilko and Hallikas, 2012). They are discussed in detail as follows.

- Visibility

Both academia and industry have identified that the visibility of risk is a major consideration in supply chain risk management (Caridi et al., 2014). This is because good visibility in a supply chain will benefit operational efficiency, productivity, and effective planning (e.g. Smaros et al., 2003; Petersen, Ragatz, and Monczka, 2005; Yu and Goh, 2014), as well as enhance supply chain stability and mitigate the bullwhip effect (Ouyang, 2007). Furthermore, case studies conducted by Harland, Brenchley, and Walker (2003) indicated that more than half of the risks influencing the studied companies were associated with the lack of sufficient visibility in the supply chains, and the situation becomes more worrisome given the increasing use of “virtual” supply chains. Enslow (2006) found that more than three quarters of the large companies in a global survey identified the lack of supply chain visibility as their top concern.

Visibility can be treated as the outcome of external integration. To some extent, it reflects co-operation among partner firms, in terms of information/knowledge within a supply chain (Vilko, Ritala, and Hallikas, 2016). Internet of things (IoT) technologies (e.g., electronic product code (EPC), and radio frequency identification (RFID)) have facilitated information sharing among actors in a supply chain. This enables the monitoring of the status of cargo shipments, improving the visibility and connectivity of the entire supply chain (Zhou et al., 2009). These tools significantly contribute to reducing supply chain uncertainty, facilitating more stringent control of product inventory.

Risk visibility is also expressed in other forms. Cats, Yap and van Oort (2016) explored the role of exposure in risk analysis in the context of transport networks. The results showed that including exposure allows forecasting network link criticality, so the assessment of disruption effects can be embedded in a cost-benefit analysis. In an FMEA model, risk visibility is measured using an indicator called "detection": the means or methods by which a failure is detected, and the time it needs (Pentti and Atte, 2002). In this paper, the risk visibility indicates the level of awareness of the risk factors to be estimated, and how easily managers can detect them during regular risk checks.

- Consequence

In recent research of risk analysis in container shipping operations, Chang, Xu, and Song (2015) considered three types of risk consequences when developing risk maps: financial loss, reputation loss, and safety and security incident related loss. Vilko and Hallikas (2012) also described three types of risk consequences in the field of supply chain risk management: time-based, finance-based, and quality-based effects. Time-based effects included the delay and disruption of material or information flows of a supply chain; finance-based effects usually influenced financial flows, leading to cost increases or lost profits; and the quality-based effects referred to the damaged quality of cargo, service, or equipment. In this thesis, the risk consequence is subdivided into three categories based on the nature of its impact, which are time delay/disruption, additional cost, and quality damage (or damage to quality).

Delays cause pressure on the schedule flexibility of liner shipping and decrease liner service reliability. Due to the complex and variable navigation environment, maritime transportation can be delayed for days or even a week without serious consequences (Vilko and Hallikas, 2012). Generally, there is no clear time limitation on delays, and the severity of time delays varies significantly, depending on the cargo being transported. For example, a shipping delay of time- and temperature-sensitive products will have more severe consequences than that of normal goods. Here, disruption is identified as a breakdown in a maritime supply chain, where minimum requirements cannot be achieved. The parameter time delay/disruption has been widely studied in the context of container shipping (e.g. Chang, Xu and Song, 2014; Notteboom, 2006; Vilko, Ritala and Hallikas, 2016). Additional costs include costs associated with additional operations and management (such as additional inventory costs and production costs), and fees attributable to risk drivers. For example, these costs include fees spent to hire armed guards on ships to protect cargo on routes with a high possibility of piracy attack (Willis, 2011). Quality damage refers to the damage to any component within an MSC, including transported goods, port infrastructure, and container vessels.

In spite of the clear differences as discussed among the consequence-related risk parameters, it should be noted that there are still overlaps among them, and thus they are not completely exclusive and independent from each other. For example, a maritime traffic incident such as a ship collision may cause damage to ships or even cargo, and at the same time, there is a high probability that the influenced shipping will be delayed.

4.2.2 Fuzzy Rule-based Systems

A rule-based system is composed of a set of fuzzy IF-THEN rules that relate input to output variables, and the rules are usually defined relative to the context and situation of problems (Khuankrue et al., 2017). The *k*th IF-THEN rule in a conventional rule base can be expressed in the following form (Yang, Bonsall and Wang, 2008):

$$R_k: \text{ IF } A_1^k \text{ and } A_2^k \text{ and...and } A_M^k, \text{ THEN } D_k \qquad \text{Eq. 4.1}$$

where $A_i^k (i = 1, \ldots, M)$ is a referential value of the *i*th antecedent attribute in the *k*th rule, and M is the number of the antecedent attributes used in the *k*th rule. D_k ($\in D$, the set of all consequents) is the consequent in the *k*th rule. Obviously, the IF-THEN rules consist of two parts: an antecedent part that responds to the input variable(s) and a consequent part describing the corresponding values of the outputs. These fuzzy rules can be derived from both experts' reasoning and domain knowledge.

As shown in Eq.4.1, the case of single output is usually considered in a classical fuzzy rule-based system. While the traditional rule base is constructed to represent fuzziness, this kind of fuzzy system composed of such simple IF-THEN rules has been criticised due to the fact that the consequent part lacks sensitivity against the antecedent part in real-world applications. In other words, it means that the consequence may sometimes not be able to respond to slight changes of linguistic variables occurring in the antecedents. A good example to illustrate this deficiency can be found in its application in the FMEA for safety assessment, shown as follows (Yang, Bonsall, and Wang, 2008):

> R_1: IF *occurrence likelihood* of a risk factor is “very low” ($L1$) AND *consequence severity* is “negligible” ($C1$) AND *probability of failures being undetected* is “highly unlikely” ($P1$), THEN the *safety level* is “good” ($S1$).
>
> R_2: IF *occurrence likelihood* of a risk factor is “very low” ($L1$) AND *consequence severity* is “negligible” ($C1$) AND *probability of failures being undetected* is “unlikely” ($P2$), THEN the *safety level* is “good” ($S1$).

It can be seen that a slight input change from $P1$ to $P2$ cannot be reflected in the output. In addition, in a traditional IF-THEN rule base, inputs and outputs are usually expressed with 100% certainty, resulting in other obvious deficiencies including the limited power of representing knowledge in the real world and not being able to deal with other types of uncertainties such as ignorance and incompleteness. Thus, a new knowledge representation scheme in a rule base has been proposed to enhance its ability of processing uncertainties in a complex system, which will be elaborated in the following section.

4.2.3 Belief Rule-based Methods and Its Application

4.2.3.1 FRB with a belief structure

In order to model a complex environment and handle uncertain information in the risk management of supply chains, the classical fuzzy rule-based systems are extended by incorporating the concept of DoB into the consequent parts of traditional IF-THEN rules (Yang et al., 2006). The belief rule expressions in a fuzzy rule-based system can provide a better compact framework for expert knowledge representation, enabling it to deal with the situation where evidence available is not enough or experts are not 100% certain of their judgements but possess only degrees of belief or credibility regarding a hypothesis (Yang et al., 2006).

Three important concepts that should be taken into account to support such an extension are the distribution of DoB in a consequent, attribute weights, and rule weights. DoB in a consequent indicate the experts’ opinions on the extent to which a consequence value may be within the set of all consequents; the weight of an attribute expresses its relative importance regarding its influence on the consequence of a rule; and the weight of rule represents its relative importance to the associated conclusions, reflecting the reliability of the rule (Tang et al., 2011). Based on that, the simple rule as expressed in Eq.4.1 can be extended to a so-called belief rule with all possible consequents associated with belief degrees, as shown in Eq. 4.2 (Yang et al., 2006).

$$\begin{aligned} R_k:\ & \text{IF } A_1^k \text{ and } A_2^k \text{ and...and } A_M^k, \\ & \text{THEN } \{(D_1,\beta_1^k),(D_2,\beta_2^k),\ldots,(D_N,\beta_N^k)\} \\ & \left(\sum_{j=1}^{N}\beta_j^k \le 1\right) \end{aligned} \qquad \text{Eq. 4.2}$$

where, $\beta_j^k (i = 1,2,\ldots,N)$ is the DoB to which D_j is believed to be the consequent in the *k*th packet rule, when the input satisfies the antecedents $A^k = \{A_1^k, A_2^k, \ldots, A_M^k\}$. *N* is the number of all possible consequents. If $\sum_{j=1}^{N}\beta_j^k = 1$, the *k*th rule is considered to be complete; otherwise, it is incomplete. A belief rule base (BRB) is a collection of such belief rules. For comparison purpose, similar rules as described in Section 4.2.2 are presented as follows to show the advantages of belief rules (Yang, Bonsall, and Wang, 2008):

R_1: IF *occurrence likelihood* of a risk factor is “very low” (*L*1) AND *consequence severity* is “negligible” (*C*1) AND *probability of failures being undetected* is “highly unlikely” (*P*1),

THEN the *safety level* is {(good (*S*1), 1), (average (*S*2), 0), (fair (*S*3), 0), (poor (*S*4), 0)}.

R_2: IF occurrence likelihood of a risk factor is “very low” (L1) AND consequence severity is “negligible” (C1) AND probability of failures being undetected is “unlikely” (P2),

THEN the *safety level* is {(good (*S*1), 0.91), (average (*S*2), 0.09), (fair (*S*3), 0), (poor (*S*4), 0)}.

where {(good, 0.91), (average, 0.09), (fair, 0), (poor, 0)}is a DoB distribution representation for safety level consequent, indicating that it is 91% sure that the safety level is good and 9% sure that the safety level is poor. In this example of belief rule, the total DoB is 0.91+0.09=1, so that the assessment is complete.

4.2.3.2 Application of BRB systems

The BRB methodology is described as being capable of capturing the relationships between system inputs and outputs that could be discrete or continuous, complete or incomplete, linear or nonlinear, linguistic or numerical, or their mixture (Yang et al., 2006). Some major advantages of a BRB over traditional rule-based systems are, for example, in a BRB, the consequence of a rule is presented in the form of belief degrees distribution so that any changes in antecedent attributes can be clearly reflected in the consequence part. Besides, with the help of input transformation techniques (Yang, 2001), different types of inputs collected from multi sources with different features can be handled in a consistent manner in a BRB. Thus, the BRB model will be more informative, more flexible, and closer to the reality (Tang et al., 2011). However, due to the special structure of belief rules, traditional fuzzy logic reasoning methods developed based on the fuzzy set operations, are no longer suitable for the inference in BRB systems. In view of this, other approaches are introduced and incorporated into the BRB system to facilitate its application.

Zhou et al. (2010) combined the BRB with the hidden Markov model (HMM) to achieve the real-time prediction of hidden failures of a system, in which the BRB is used to model the relationships between the environmental factors and the transition probabilities of the hidden states of the system, while the HMM is used to capture the relationships between the hidden failures and observations of a system. Based on a BK-tree, Su et al. (2016) proposed a structure optimization framework to improve the reasoning efficiency and decision accuracy of the extended BRB system. In another research, Aminravan et al. (2013) employed a novel proposed networked fuzzy BRB system to design decision support tools for relative water quality assessment in the distribution network. A learning algorithm was also incorporated to find the locally optimum parameters of the networked fuzzy BRB system. Among them, one of the widespread applications of the BRB that is worth mentioning is the generic rule-based inference methodology using the evidential reasoning (RIMER) approach, which is short for the Rule-base Inference Methodology using the Evidential Reasoning approach (Yang et al., 2006). The inference procedure the RIMER approach is basically composed of three main steps, which are input transformation, activation of rule weights, and rule inference using evidential reasoning approach (Chen et al., 2011). Owing to the superiorities in dealing with complex reasoning problems under uncertainty, its related application can be found in a variety of fields such as environmental impact assessment, multi-attribute decision (Xu, Yang and Wang, 2006), engineering failure detection (Zhou et al., 2009), and risk analysis in offshore and maritime engineering (Ren et al., 2009), etc. However, one possible disadvantage of the RIMER approach that may hinder its development in practice is the complex calculation process it involves, which is argued to be not friendly to mathematically unsophisticated users (Yang, Bonsall and Wang, 2008). Therefore, Bayesian networks (BNs), another important and popular method for modelling uncertainties, are introduced to BRB systems in order to enhance their applicability in risk analysis and decision making without compromising the easiness and transparency.

An important application of BNs in BRB was conducted by Yang, Bonsall and Wang (2008). In the research, a new hybrid methodology was proposed to deal with some of the drawbacks regarding the use of conventional fuzzy rule-based methods in FMEA. The BN was incorporated into FRB risk inference in a complementary way, in which the subjective belief degrees were assigned to the consequent part of the rules to model the incompleteness encountered in establishing the knowledge base, and a Bayesian reasoning mechanism was then used to aggregate all relevant rules for assessing and prioritising potential failure modes. The new approach is tested by using a benchmarking technique with the RIMER approach, and its applicability was demonstrated by a series of case studies of collision risk in offshore engineering. After that, the proposed method has also led to many new applications including the selection of suitable steaming speed of container ships (Rahman et al., 2012), pipeline leak detection (Hu et al., 2011), risk analysis of academic research laboratories (Plüss, Groso and Meyer, 2013), supplier selection in a global sourcing environment, and assessing and prioritising risk factors in ports (Yang, Ng and Wang, 2013; Alyami et al., 2014), to name but a few.

4.3 Use of BN to Model BRB for Risk Assessment of MCSCs

Due to the lack of objective data on risk management in the container shipping industry, a novel subjective knowledge-based approach is proposed to conduct in-depth risk evaluation in MCSCs, which is called a belief rule-based Bayesian network (BR-BN) approach. In the BR-BN approach, the relationships between risk parameters and risk status are modelled and represented in the form of a rule base with belief structure, and the belief degrees in the rule base are then transformed into subjective conditional probabilities in Bayesian networks, so that the advantages of both fuzzy rule-based systems and BN techniques in modelling and processing multi-source information under uncertain environment can be effectively taken. The proposed methodology consists of six major components, which outline all the necessary steps required for risk assessment (as shown in Figure 4.1). They include:

Step 1. Identification of risk factors in MCSCs;

Step 2. Establishment of the BRB for risk assessment;

Step 3. Risk factors estimation and data collection;

Step 4. Risk inference using a BN technique;

Step 5. Prioritisation of risk factors with utility functions; and

Step 6. Validation of the results.

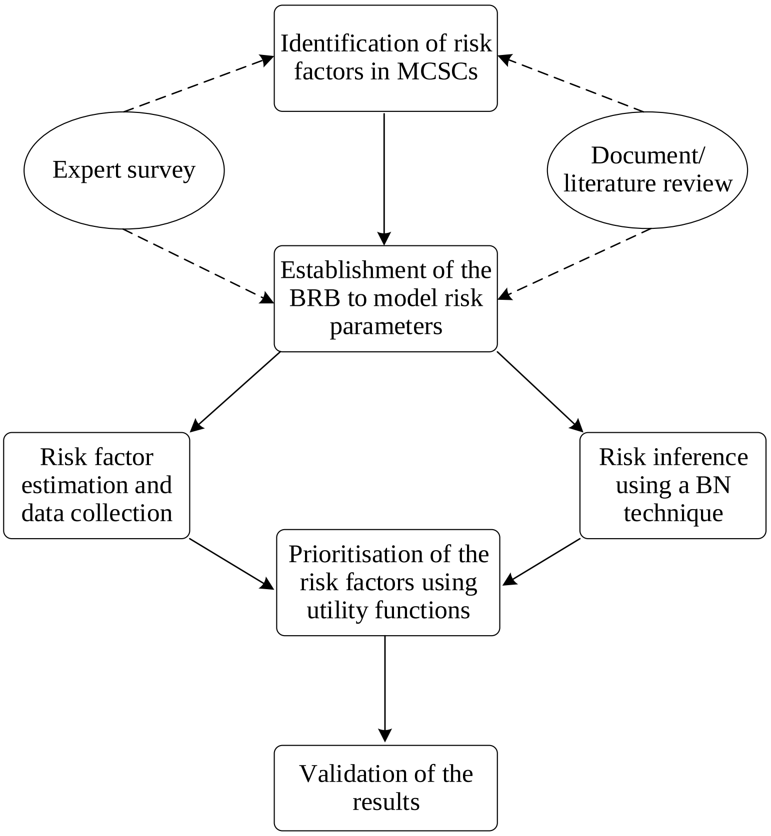

Figure 4.1. The research methodology of risk factors prioritisation in MCSCs

4.3.1 Identification of Risk Factors in MCSCs

Identification of risk factors is normally recognised as a starting point of the risk assessment process, and it is critical to the success of supply chain risk management. The MCSC in the research refers to the part of a supply chain in relation to the business of maritime logistics of containers, which is mainly composed of container port/terminal operations and seaborne transportation. Besides, external and internal influence from the upstream/downstream of the sections is also considered. The risk factors are identified with respect to different risk types originated from various sources. Detailed information of risk identification and classification can be found in Chapter 3 for reference. The top ten risk factors selected with a consideration of both their occurrence likelihood and consequence severity are considered for a case study in this chapter.

4.3.2 Establishment of the BRB for Risk Assessment of MCSCs

This step is to construct the BRB for risk assessment of MCSCs using Eq. 4.2. To construct such systems, five risk parameters are considered as the antecedent attributes in fuzzy rules (the IF part), which are risk occurrence likelihood (*L*), visibility (*V*), consequence severity in terms of time delay/disruption (*CT*), consequence severity in terms of additional cost (*CC*), and consequence severity in terms of quality damage (*CQ*). Risk status (*R*) is presented as the consequent attribute (the THEN part). DoBs are assigned to the linguistic variables used to describe the consequent attribute *R* in the BRB. To facilitate subjective data collection and representation of judgements on the five antecedent attributes and conclusion, a set of suitable linguistic variables are defined. The linguistic variables for describing each attribute are decided according to the situation of the case of interest. A literature survey suggests that the linguistic variables employed to describe risk parameters *L*, *V*, *CT*, *CC*, and *CQ* in the container shipping industry may be defined as follows (Alyami et al., 2014; Alyami et al. 2016; Vilko, Ritala, and Hallikas, 2016). To estimate *L*, one may often use variables (*Li*, *i* =1, 2, 3) like "unlikely", "occasional", and "frequent". Variables (*Vj*, *j* =1, 2, 3) used to estimate *V* are often "poor", "normal", and "good"; variables (*CTk*, *k* =1, 2, 3) used to estimate *CT* are often "low", "medium", and "high"; variables (*CCl*, *l* =1, 2, 3) used to estimate *CC* are often "low", "medium", and "high"; and variables (*CQm*, *m* =1, 2, 3) used to estimate *CQ* are often "negligible", "moderate", and "critical". Similarly, the risk status can be described using such linguistic variables (*Rh*, *h* =1, 2, 3) as "low", "medium", and "high". The definitions of linguistic variables of all risk parameters are obtained taking into account the knowledge from both literature and domain experts, as summarised in Table 4.1.

Table 4.1. Definitions of linguistic grades of each risk parameter

Parameter	Linguistic grades	Definition
Likelihood	Unlikely	Occurs less than once per year
	Occasional	Expected to occur every few months
	Frequent	Expected to occur at least monthly
Visibility	Poor	Impossible or difficult to be detected through intensive risk checks
	Normal	Possible to be detected through intensive risk checks
	Good	Possible to be detected through regular risk checks
Time delay/ disruption	Low	A delay less than 24 hours in total
	Medium	A delay but no more than 20% of the original schedule
	High	A delay of more than 20% of the original schedule
Additional cost	Low	An additional cost no more than 10% of the total cost
	Medium	An additional cost between 10% and 50% of the total cost

	High	An additional cost of more than 50% of the total cost
Quality damage	Negligible	Slight cargo, equipment, or system damage but fully functional and serviceable
	Moderate	Minor incapability of systems or equipment and a small portion of goods may be damaged
	Critical	Damage/loss of major systems or equipment, and serious damage to the transported goods

The number of linguistic grades for each risk parameter should not necessarily be the same, and more linguistic variables can also be applied according to the requirement under different circumstances (examples can be found in the research by Yang, Bonsall and Wang (2008)). However, it is worth noting that the number of rules in a BRB is directly proportional to the number of linguistic variables of each antecedent attribute, indicating that the rule number will be multiplied with the increase of variable number, which may largely weaken its practicability in industrial application.

Regarding the conclusion part of a BRB, the DoB of the rules can be assigned based on knowledge accumulated from past events (Alyami et al., 2014) or directly by using multiple expert knowledge (Yang et al., 2009). However, in practice, it is difficult to determine all the DoBs of rules accurately in a BRB by using only experts' subjective knowledge, especially for a large-scale BRB with hundreds or even thousands of rules. In view of this, a proportion method was proposed by Alymai et al. (2014) to rationalise the distribution of DoB. It provides a logical and straightforward way to calculate the DoB in the THEN part. However, one major deficiency of the research is the ignorance of the weight of risk parameters when calculating the DoB. This may impair the accuracy of the results, as any change in an attribute weight may lead to significant changes in the performance of the BRB systems. Thus, the relative importance of the antecedent attributes should be appropriately considered in the process of developing a rule representation. In this research, the weight of each risk parameter is calculated by using an AHP method, and the results are shown in Table 4.2 (the sample questionnaire used to collect expert opinions on the relative importance of each risk parameter is listed in Appendix Four). The relative importance of each risk parameter is taken into consideration when approaching the DoB distribution on the basis of the proportion method. Observing that all attributes in both IF part and THEN part are described by variables with three grades, thus, for any specific conclusion attribute, its DoB belonging to a particular grade can be calculated by summing up the normalised weights of all risk parameters that receive the "same" grade. Take *Rule* 2 as an illustration:

- *Rule* #2: If *L* is *Unlikely, V* is *Good, CT* is *Low, CC* is *Low*, and *CQ* is *Moderat*e, then *R* is *Low* with a 69% DoB, *Medium* with a 31% DoB and *High* with a 0% DoB.

The total weights of all risk parameters holding the Low (or equivalent) and the Medium (or equivalent) grades are 0.69 (0.18+0.08+0.35+0.08) and 0.31 (CQ, 0.31), respectively. The DoBs belonging to Low and Medium in the R are therefore 69% and 31%, respectively. Similarly, the BRB used in risk assessment of MCSCs containing 243 (3 × 3 × 3 × 3× 3) rules has been developed and listed in Appendix six (such a rule base represents functional mappings between antecedents and conclusions).

Table 4.2. The weight of each risk parameter in the BRB

Risk parameters (antecedent attribute)		Local weight		Global weight
Occurrence likelihood (L)		0.18		0.18
Visibility (V)		0.08		0.08
Consequence severity	Time delay (CT)	0.74	0.47	0.35
	Additional cost (CC)		0.11	0.08
	Quality damage (CQ)		0.42	0.31

4.3.3 Risk Factors Estimation and Data Collection

This step is to estimate the risk parameters in the antecedents in terms of each identified risk factor by using the defined linguistic variables, collect subjective data from experts, and transform them into a unified form if needed, so that they can be appropriately used in a BRB system for risk inference. In a traditional FRB system, membership functions are generally used to model linguistic variables. Some typical inputs (e.g. a single deterministic value, a triangular distribution, and a trapezoidal distribution) may be encountered due to the possible uncertainties involved (Eleye-Datubo, 2004) and they are usually represented using fuzzy membership functions based on historical data or experts' experience (Yang, Bonsall and Wang, 2008). A mapping function method (Liu et al., 2004) is usually incorporated to transform the inputs into probability distributions of linguistic variables in antecedents. However, some researchers argued that such observation transformation operations might be debatable given that the risk analysis results are sensitive to the qualitative judgment of the linguistic variables used (e.g. Braglia, Frosolini and Montanari, 2003; Yang, Bonsall and Wang, 2008). Thus, a subjective probability method is employed in this study to overcome the possible weakness, in which the linguistic variables are treated as independent value sets without fuzzy membership functions being involved.

Subjective probability is a probability derived from an expert's judgment about the degrees of a specific linguistic variable that one risk parameter belongs to. It reflects one's opinions and past experience. In the subjective probability method, risk parameters are estimated and represented using the probability distribution of the linguistic variables, which can be given by experts directly. For example, the L of one risk factor is estimated by experts as *"Unlikely" with 0.7 subjective probability, and "Occasional" with 0.3 subjective probability*. The subjective probability distribution from multiple expert judgments can be merged using a weighted average based on the relative importance of each expert. In this study, a questionnaire survey is conducted to collect experts' judgement of risk parameters in terms of the selected MCSC. The questionnaire used is listed in Appendix Five.

4.3.4 Risk Inference Using a BN Technique

Once all the data needed has been collected and prepared, a BN technique can be applied to conduct risk inference. Since multiple rules will be used in risk assessment for a particular risk factor, BN can serve as an appropriate tool to synthesise the DoBs of different rules involved due to its ability in capturing non-linear causal relationships (Alymai et al., 2104). To achieve the rule aggregation, the BRB developed in Section 4.3.2 is firstly represented in the form of conditional probabilities. For example, Rule 2 in Appendix Six can be displayed using Eq. 4.2 as the following:

R_2: IF *Unlikely* ($L1$), *Good* ($V1$), *Low* ($CT1$), *Low* ($CC1$), and *Moderate* ($CQ2$),
THEN {(*Low* ($R1$), 0.69), (*Medium* ($R2$), 0.31), (*High* ($R3$), 0)}.

It can be further represented in the form of conditional probability as follows.

Given $L1$, and $V1$, and $CT1$, and $CC1$, and $CQ2$, the probability of Rh ($h = 1, 2, 3$) is (0.69, 0.31, 0), or

$$p\,(Rh \mid L1, V1, CT1, CC1, CQ2) = (0.69, 0.31, 0) \qquad \text{Eq. 4.3}$$

where "|" symbolizes conditional probability.

Using a BN technique, the BRB constructed in Section 4.3.2 can be modelled and converted into a converging connection consisting of six nodes- five parent nodes, which are N_L, N_V, N_{CT}, N_{CC}, and N_{CQ} (Nodes L, V, CT, CC and CQ); and one child node, which is N_R (Node R). Having transferred the BRB into a BN, the rule-based risk inference for the risk assessment will be simplified as the calculation of the marginal probability of the node N_R. To marginalize R, the required CPT of N_R, $p\,(R \mid L, V, CT, CC, CQ)$ can be obtained using Eq. 4.3, and the BRB is shown in Appendix Six. It indicates a 3 × 3 × 3 × 3 × 3 table containing values $p\ (Rh \mid Li, Vj, CTk, CCl, CQm)$ (h, i, j, k, l, m = 1, 2, 3), as shown in Table 4.3.

Risk assessment of each risk factor can be realised using subjective judgments from experts based on real observations with respect to the five risk parameters and associated linguistic grades as presented in Table 4.1. Subjective probabilities β_i obtained from observations can be considered as the prior probabilities of node N_L, $p\ (Li)$. Similarly, the prior probabilities of all parent nodes, N_V, N_{CT}, N_{CC}, and N_{CQ}, can be computed as $p\ (Vj) = \beta_j$, $p\ (CTk) = \beta_k$, $p\ (CCl) = \beta_l$, and $p\ (CQm) = \beta_m$, respectively. Then, the marginal probability of N_R can be calculated using Eq. 4.4 (Jensen and Nielsen, 2007).

$$p(Rh) = \sum_{i=1}^{3}\sum_{j=1}^{3}\sum_{k=1}^{3}\sum_{l=1}^{3}\sum_{m=1}^{3} p(Rh \mid Li, Vj, CTk, CCl, CQm)\, p(Li)\, p(Vj)\, p(CTk)\, p(CCl)\, p(CQm) \quad \text{Eq. 4.4}$$

$$(h = 1, 2, 3)$$

Table 4.3. The conditional probability table of N_R

L	L1																														
V	V1																V3														
CT	CT1								CT3								CT1								CT3						
CC	CC1				CC3				CC1				CC3				CC1				CC3				CC1				CC3		
CQ **R**	CQ1		CQ3		CQ1		CQ3	…	CQ1		CQ3		CQ1		CQ3	…	CQ1		CQ3		CQ1		CQ3	…	CQ1		CQ3		CQ1		CQ3
R1	1	…	0.69	…	0.92	…	0.61		0.65	…	0.34	…	0.57	…	0.26		0.92	…	0.61	…	0.84	…	0.53		0.57	…	0.26	…	0.49	…	0.18
R2	0		0		0		0		0		0		0		0		0		0		0		0		0		0		0		0
R3	0		0.31		0.08		0.39		0.35		0.66		0.43		0.74		0.08		0.39		0.16		0.47		0.43		0.74		0.51		0.82
	. . .																														
L	L3																														
V	V1																V3														
CT	CT1								CT3								CT1								CT3						
CC	CC1				CC3				CC1				CC3				CC1				CC3				CC1				CC3		
CQ **R**	CQ1		CQ3		CQ1		CQ3	…	CQ1		CQ3		CQ1		CQ3	…	CQ1		CQ3		CQ1		CQ3	…	CQ1		CQ3		CQ1		CQ3
R1	0.82	…	0.51	…	0.74	…	0.43		0.47	…	0.16	…	0.39	…	0.08		0.74	…	0.43	…	0.66	…	0.35		0.39	…	0.08	…	0.31	…	0
R2	0		0		0		0		0		0		0		0		0		0		0		0		0		0		0		0
R3	0.18		0.49		0.26		0.57		0.53		0.84		0.61		0.92		0.26		0.57		0.34		0.65		0.61		0.92		0.69		1

4.3.5 Prioritisation of Risk Factors with Utility Functions

In order to prioritise the risk factors, appropriate utility values U_{Rh} are required so that the DoBs of risk status can be transformed into crisp values for the comparison purpose. The utility values can be defined based on the combination of some specific fuzzy rules (Wang, Yang and Sen, 1995) and risk scores by satisfying the following conditions.

1) IF Unlikely (L1), Good (V1), Low (CT1), Low (CC1), and Negligible (CQ1),

THEN {(*Low* (*R*1), 1), (*Medium* (*R*2), 0), (*High* (*R*3), 0)}.

2) IF Occasional (L2), Normal (V2), Medium (CT2), Medium (CC2), and Moderate (CQ2),

THEN {(*Low* (*R*1), 0), (*Medium* (*R*2), 1), (*High* (*R*3), 0)}.

3) IF Frequent (L3), Poor (V3), High (CT3), High (CC3), and Critical (CQ3),

HEN {(*Low* (*R*1), 0), (*Medium* (*R*2), 0), (*High* (*R*3), 1)}.

The risk score (*RS*) describes the individual grade of each linguistics term *Li*, *Vj*, *CTk*, *CCl*, or *CQm* ($i, j, k, l, m = 1, 2, 3$) using a number in the scale [1, 3], where 1 indicates the “lowest level” (contributing the least to final risk status), and 3 means the “highest level” (contributing the most to final risk status). For instance, $RS\,(L1) = 1$, $RS\,(V2) = 2$, $RS\,(CC3) = 3$. Consequently, the values of U_{Rh} can be calculated as,

$U_{R1} = RS\,(L1) \times RS\,(V1) \times RS\,(CT1) \times RS\,(CC1) \times RS\,(CQ1) = 1^5 = 1$

$U_{R2} = RS\,(L2) \times RS\,(V2) \times RS\,(CT2) \times RS\,(CC2) \times RS\,(CQ2) = 2^5 = 32$

$U_{R3} = RS\,(L3) \times RS\,(V3) \times RS\,(CT3) \times RS\,(CC3) \times RS\,(CQ3) = 3^5 = 243$

Thus, a new risk priority index (*RPI*) can be developed by Eq. 4.5.

$$RPI = \sum_{h=1}^{3} p(Rh)U_{Rh} \qquad \text{Eq. 4.5}$$

where the larger the value of *RPI*, the higher the risk status of a risk factor.

4.3.6 Validation Using Sensitivity Analysis

When a new model is developed, a careful test is required to test its soundness. It is especially important and desirable when subjective elements are involved in the evaluation process based on the proposed model. In this study, a sensitivity analysis is conducted to test the accuracy of the belief structures, and logicality of the BR-BN method proposed. Sensitivity analysis provides an analytical judgment for *RPI*. It refers to checking how sensitive the outputs (the risk assessment results or *RPI*) are to minor changes in inputs (judgments of the risk parameters). If the BRB is reliable and the proposed model is sound, then the sensitivity analysis must at least follow the following three axioms (Yang, Bonsall and Wang, 2008; Alyami et al., 2014).

Axiom 1. A slight increase/decrease in the prior subjective probabilities of each input node should certainly result in the effect of a relative increase/decrease of the posterior probability values of the output node.

Axiom 2. Given the same variation of subjective probability distributions of each risk parameter in the antecedents, its influence magnitude to the *RPI* will keep consistency with their weight distributions.

Axiom 3. The total influence magnitudes of the combination of the probability variations from x attributes (evidence) on the *RPI* should always be greater than the one from the set of $x - y$ ($y \in x$) attributes (sub evidence).

4.4 Case study

In this section, an anonymous container shipping company (one of the top three container shipping companies in China) was selected to conduct the risk assessment on one of its MCSCs as a case study in order to demonstrate the feasibility of the proposed method.

4.4.1 Selection of Major Risk Factors

In Chapter 3, altogether 64 risk factors in MCSCs were identified and classified into four distinguishing groups according to the values of their *ARI*s by using a risk matrix analysis. Those risk factors which are recognised to have a relative high ARI value are selected for further risk assessment in this chapter. They are “fierce competition”, “fluctuation of fuel price”, “change of exchange rates”, “unattractive markets”, and “transportation of dangerous goods”.

4.4.2 Establishment of the Appropriate BRB

The detailed information on the construction of the BRB can be found in Section 4.3.2, and it is used in the case study. It is noteworthy that such a rule base provides a standard, generic belief structure. It is obvious that the DoBs of each individual rule can be reassigned with some flexibility to suit various specific applications in different supply chains. However, the inputs from multiple domain experts, as well as appropriate verification would be necessary and significant to ensure practical and non-biased belief functions (Yang, Bonsall and Wang, 2008).

4.4.3 Use of Questionnaire Survey to Estimate the Major Risk Factors

A questionnaire was designed (see Appendix Five) to collect risk assessment information on the five major risk factors from three experienced staff, who work cooperatively for the safe and efficient operation of the investigated shipping route. The three experts have been actively working at the investigated shipping line for more than ten years, and their basic information is described as the following.

- Expert No.1: Senior captain, head of technical safety department, who has been working on board ships at the investigated shipping line for more than 12 years.
- Expert No.2: Senior officer, head of marine operations centre, involved in the safety and security management of global container fleets in the shipping company with 12 years' experience.
- Expert No.3: Senior manager, deputy director of the operations and emergency services division, who has been working for more than 15 years in the shipping company.

The feedback received from the three experts is combined using a weighted average. Referring to the similar seniority of the three experts selected for the case study, the relative weight of every expert is assigned equally when merging their judgments of risk parameters in terms of each risk factor. The average inputs will be used in the BR-BN method to rank the five major risk factors. Taking the "fierce competition" as an illustration, the assessment values of the five risk parameters are obtained and calculated, as shown in Table 4.4.

Table 4.4. Experts evaluation results of "fierce competition"

Risk parameters	Experts			Combined DoBs
	No.1	No.2	No.3	
L	10% Unlikely 30% Occasional 60% Frequent	0% Unlikely 20% Occasional 80% Frequent	0% Unlikely 35% Occasional 65% Frequent	3.3% Unlikely 28.3% Occasional 68.4% Frequent
V	40% Good 40% Normal 20% Poor	70% Good 30% Normal 00% Poor	60% Good 40% Normal 0% Poor	56.6% Good 36.7% Normal 6.7% Poor
CT	80% Low 20% Medium 0% High	80% Low 20% Medium 0% High	0% Low 80% Medium 20% High	53.3% Low 40.0% Medium 6.7% High
CC	30% Low 60% Medium 10% High	20% Low 80% Medium 0% High	30% Low 50% Medium 20% High	26.7% Low 63.3% Medium 10.0% High
CQ	80% Negligible 20% Moderate 0% Critical	100% Negligible 0% Moderate 0% Critical	70% Negligible 30% Moderate 0% Critical	83.3% Negligible 16.7% Moderate 0% Critical

Estimation results of all risk parameters in terms of each risk factor can be transformed into the format of prior probability by using Eq. 4.3, and the BR-BN method can then be applied to conduct risk inference.

4.4.4 Use of BR-BN Method for Risk Inference

Still, taking the risk factor "fierce competition" as an example, the risk status of "fierce competition" can be calculated using Eq. 4.4 as $p(Rh)$ = (51.7%, 32.3%, 16%), in which 162 out of 234 rules in the established BRB are fired during the particular calculation process. The result can also be expressed as {(*Low*, 51.7%), (*Medium*, 32.3%), (*High*, 16%)}, and explained as that the risk status associated with the "fierce competition" is low with a 51.7% DoB, medium with a 32.3% DoB, and high with a 16% DoB. The calculation can be modelled using *GeNle 2.0* software to facilitate BN computation, see an example in Figure 4.2.

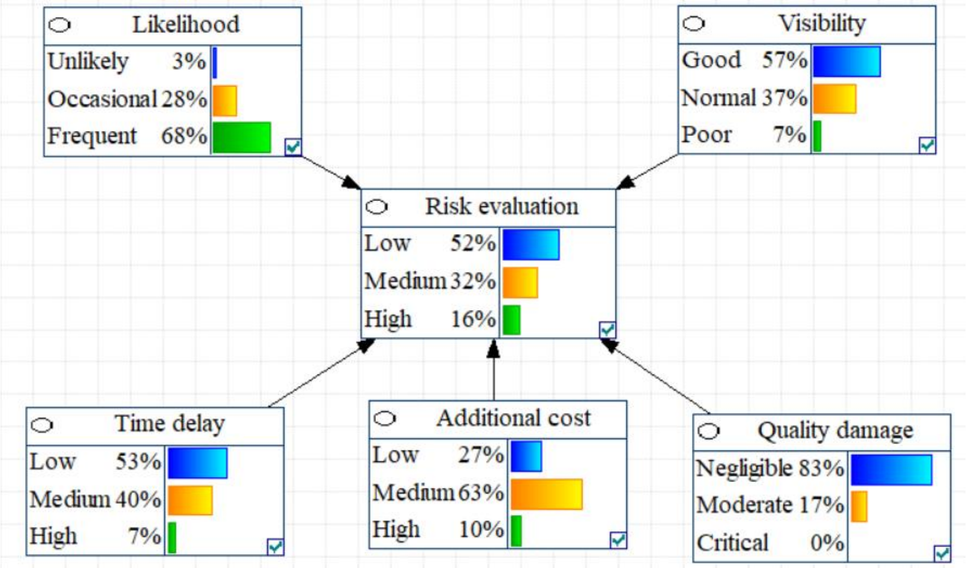

Figure 4.2. Risk assessment of "fierce competition" using *GeNle 2.0* software

As shown in Figure 4.2, any risk input related to the five risk parameters can trigger a change in the output node, which helps to realise the automation of instant risk assessment of any target risk factors within an MCSC. In a similar way, the risk status of other risk factors can be obtained, listed as follows.

The risk status of "fluctuation of fuel price"

= {(Low, 58%), (Medium, 27.3%), (High, 14.7%)};

The risk status of "change of exchange rates"

= {(Low, 62.6%), (Medium, 20.8%), (High, 16.6%)};

The risk status of “unattractive markets”

= {(Low, 62.8%), (Medium, 21.1%), (High, 16.1%)};

The risk status of “transportation of dangerous goods”

= {(Low, 32.9%), (Medium, 52.7%), (High, 14.4%)}.

4.4.5 Prioritisation of the Major Risk Factors

The risk status of risk factors expressed by linguistic variables with DoBs requires further analysis by assigning them appropriate utility values for the prioritisation. By using Eq. 4.5 and the utility values obtained in Section 4.3.5, the *RPI* of risk factor “fierce competition” can be calculated as the following.

$$\begin{aligned} RPI_{fierce\ competition} &= \sum_{h=1}^{3} p(Rh)U_{Rh} \\ &= 0.517\times 1+0.323\times 32+0.16\times 243 \\ &= 49.73 \end{aligned}$$

The *RPI* of other risk factors can be obtained in a similar way. The *RPI* values of “fluctuation of fuel price”, “change of exchange rates”, “unattractive markets”, and “transportation of dangerous goods” are 45.04, 47.62, 46.50, and 52.19, respectively. Therefore, the transportation of dangerous goods in the investigated container shipping line requires more attention in the supply chain risk management compared to other risk factors. *RPI* value of all risk factors and their rankings are summarised in Table 4.5.

Table 4.5. *RPI* values of major risk factors

Risk factors	*RPI* value	Rank
Fierce competition	49.73	2
Fluctuation of fuel price	45.04	5
Change of exchange rates	47.62	3
Unattractive markets	46.50	4
Transportation of dangerous goods	52.16	1

4.4.6 Validation of the Results

The sensitivity analysis is conducted to test the robustness of the proposed BR-BN model and the logicality of the established BRB according to three axioms introduced in Section 4.3.6. Firstly, it is required to clarify the relationship between the risk status (or *RPI*) of risk factors being investigated and the five risk parameters attributes (i.e. the *L, V, CT, CC* and *CQ*). As the linguistic variables of all risk parameters hold a positive correlation with the *RPI* value, the relationship can be easily identified and described as that the *RPI* value is higher, if the linguistic variables of each risk parameter is worse (here, "worse" means, for example, a higher likelihood, time delay, additional cost, quality damage, and poorer visibility). Next, a subjective probability of 10% is reassigned in each risk parameter and moved toward the maximal increment of *RPI*. If the model reflects the logical reasoning, the *RPI* should increase accordingly. For example, if the subjective probability of the likelihood of the risk factor "transportation of dangerous goods" belonging to "frequent" increases by 0.1, and correspondingly, the subjective probability of it belonging to "unlikely" decreases by 0.1, then the *RPI* of this risk factor increases from 52.16 to 56.15. If the subjective probability of its visibility belonging to "poor" increases by 0.1, and correspondingly, the subjective probability of it belonging to "good" decreases by 0.1, then the *RPI* of this risk factor increases from 52.16 to 54.09. The similar studies have been conducted to investigate the variation between any two linguistic variables of the five risk parameters, and all the results obtained keep harmony with **Axiom 1** in Section 4.3.6. Regarding the same axiom, the consistency of the BRB can also be tested and validated by investigating the *RPI* values associated with each rule. If the BRB established in this study is sound, the value of each rule does not change abruptly with respect to variation between two neighbouring linguistic variables of each risk parameter. For example, given a set of rules in which all *L* belong to "unlikely," *V* belong to "good," *CT* belong to "low," and *CQ* belong to "negligible," the minor state variation between two neighbouring states of the risk parameter *CC* from the bottom level state "low" to the top level state "high" will deliver changes of the *RPI* values from 1 to 3.48, and then to 20.36. In a similar way, the values of all the rules in the BRB have been checked with the assistance of *GeNle 2.0* software, and the consistency and logicality of the BRB have been proved.

Such a sensitivity study reveals that the *RPI* values are sensitive to the risk parameters. However, the study based on point changes instead of interval variation (i.e. [0, 0.1]) does not well disclose the influence magnitude of the subjective probability changes of the risk parameters to the *RPI* values. To study such influence magnitude, a sensitivity analysis based on an interval [0, 0.1], where the change of a subjective probability from 0 to 0.1 with a step of 0.02 is used for each risk parameter toward the maximal increment of the *RPI*. From Figure 4.3, it is clear that the influence magnitudes of the subjective probability changes of the risk parameters to the *RPI* are significantly different. Such influence magnitudes closely follow the weight ratio among the five attributes *L*, *V*, *CT*, *CC* and *CQ* when developing the BRB, which is 0.18:0.08:0.35:0.08:0.31 (as shown in Table 4.2). This is consistent with **Axiom 2** introduced in Section 4.3.6, indicating that the rule base is reliable.

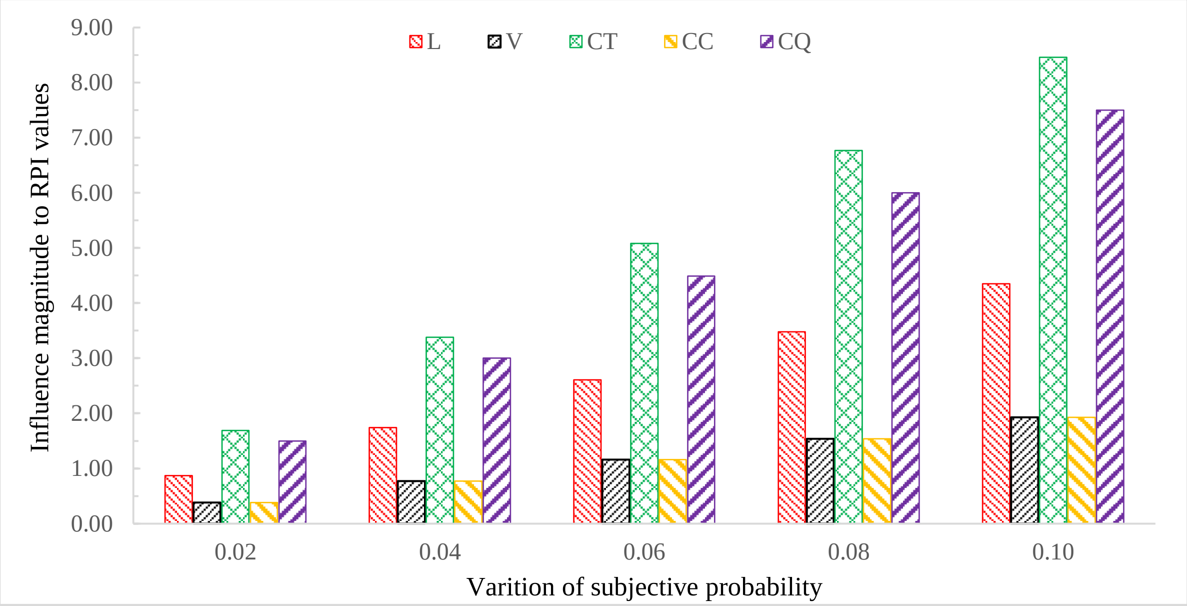

Figure 4.3. Sensitivity analysis of influence magnitudes from different attributes

While the discussion above mainly focuses on the subjective probability, in the next step, an analysis will be carried out on the effect of the variation of the risk parameters to the *RPI* values. The variation indicates the various combinations of the risk parameters. There should be altogether 31 combinations ($C_5^1 + C_5^2 + C_5^3 + C_5^4 + C_5^5$) of the five risk parameters in five groups. According to **Axiom 3** described in Section 4.3.6, if the model reflects the reality, then the influence magnitude of the five groups to values will always vary in an ascending/descending order among these groups. This can be examined by comparing the individual effects of such variations to the *RPI* values. For the illustration purpose, the assessment results of risk factor "transportation of dangerous goods" is taken as an example and a 10% subjective probability is reassigned in each risk parameter towards a maximal increment of *RPI* values. *RPI* values in terms of the influence from every combination of risk parameters along with the variations are calculated and summarised in Table 4.6.

Table 4.6. Sensitivity analysis of the influence magnitude of different combinations

Combination	**Risk parameters**					***RPI* values**	**Variation of *RPI***
	L	*V*	*CT*	*CC*	*CQ*		
#1						52.16	-
#2	O					56.51	4.35

#3		O				54.09	1.93
#4			O			60.63	8.47
#5				O		54.09	1.93
#6					O	59.66	7.50
#7	O	O				58.45	6.29
#8	O		O			64.98	12.82
#9	O			O		58.45	6.29
#10	O				O	64.01	11.85
#11		O	O			62.56	10.40
#12		O		O		56.03	3.87
#13		O			O	61.59	9.43
#14			O	O		62.56	10.40
#15			O		O	68.13	15.97
#16				O	O	61.59	9.43
#17	O	O	O			66.92	14.76
#18	O	O		O		60.38	8.22
#19	O	O			O	65.95	13.79
#20	O		O	O		66.92	14.76
#21	O		O		O	72.48	20.32
#22	O			O	O	65.95	13.79
#23		O	O	O		64.50	12.34
#24		O	O		O	70.06	17.90
#25		O		O	O	63.53	11.37
#26			O	O	O	70.06	17.90
#27	O	O	O	O		68.85	16.69
#28	O	O	O		O	74.42	22.26
#29	O	O		O	O	67.89	15.73
#30	O		O	O	O	74.42	22.26
#31		O	O	O	O	71.99	19.83
#32	O	O	O	O	O	76.36	24.20

“O”means a 10% reassignment of subjective probability in each attribute moving toward the maximal increment of *RPI*.

The combination #1 indicates a baseline of the *RPI*, which shows the original assessment result of risk factor “transportation of dangerous goods”. The 31 combinations are listed from #2 to #32, which can be grouped in five different colours. Taking combination #27 as an example (evidence), the effect of this combination on *RPI* values can be calculated as 16.69 (=68.85-52.16). Then, the influence magnitude of its sub-evidence to *RPI* values can be calculated and shown as combination #1, #2, #3, #4, #7, #8, #9, #11, #12, #14, #17, #18, #20, and #23. Comparing all the relevant inference magnitudes of such evidence and sub-evidence to *RPI* values, 16.69 is the biggest one among all selected combinations. Therefore, it can be claimed that for the investigation of the example, the model is validated to be sound. Furthermore, more investigation can be conducted in terms of other combinations and risk factors. The reasonable results being in line with **Axiom 3** are considered as a piece of evidence of the soundness and logicality of the whole model.

4.5 Conclusion

This chapter outlines a novel application of a quantitative risk evaluation method in supply chain risk management. In the BR-BN method, the BRB is established to model the relationships between risk parameters and risk status in a logical way, and the BN technique is used to conduct risk inference on the basis of the BRB. An appropriate utility function is applied to transform the DoBs of risk status into numerical values for ranking of risk factors. The Chinese container shipping company case shows that risk factor "transportation of dangerous goods" is identified as the most significant one in terms of the investigated shipping route due to its poor visibility, and high additional cost as well as severe damage to both cargo and ships if an accident occurs. This is consistency with the real-life situation in the maritime industry in China that some shippers try to hide information about the cargo in order to save money, as expensive freight and insurance are usually charged by shipping companies for the transportation of expensive cargo and dangerous goods. However, the attention being put on risk factors associated with maritime container transportation may vary, depending on, for example, the unique safety requirements of an individual shipping company, the characteristics of shipping routes being selected, and influence from the external policy environment.

The numerical case study highlights some advantages and meaningful implications of the proposed framework for risk assessment. Firstly, on the basis of traditional definitions of the risk concept, more attributes are explored to measure risk factors in MCSCs in a comprehensive and targeted way. The proper classification of risk consequence into different categories can generate useful information for managers in terms of different kinds of requirements during decision making. Secondly, the combination of fuzzy rule bases and BNs provides a powerful tool to incorporate subjective judgments for risk evaluation and prioritise risk factors when historical data is unavailable or incomplete. Besides, representation of inputs as a probability distribution on linguistic variables using a brief structure enables different types of information with uncertainty to be modelled under a unified form. Thirdly, the consideration of the weight of each antecedent attribute allows for more accurate and sound DoBs, while it maintains the easiness of proportion method at the same time when establishing the BRB (Alyami et al., 2014). Finally, the proposed method offers great potential in risk-based designing and management due to its ability to instantly rank the risk factors of a container supply chain according to the stakeholders' needs with updated information, by which the real-time requirement in the industry can also be satisfied. However, one limitation of the research which should not be ignored is that the risk assessment of the identified risk factors in this chapter is mainly conducted from a local level, without consideration of the position of ports in the MCSC. Since different ports play a different role in the container shipping network, the disruption of them will bring different impact to the whole supply chain. Thus, it is important to identify the vulnerabilities of the maritime container transportation network in order to obtain a comprehensive understanding of port position within the MCSC from a network perspective and thus put forward appropriate strategies of risk prevention and preparedness to reduce the port risk.

CHAPTER 5 - MULTIPLE CENTRALITY ASSESSMENT OF PORTS IN MARITIME CONTAINER TRANSPORTATION NETWORKS

Summary

Chapter 4 has proposed an advanced risk modelling approach for investigating the risk factors of MCSCs with respect to likelihood, visibility, and three types of risk consequence. However, this kind of risk evaluation was conducted mainly from a local perspective, mainly focusing on the MCSC with respect to aspects such as external environment, management, and operations, with the analysis of network structure of the container transportation system more or less being ignored. In order to generate a deeper understanding of MCSCs, the weight of container transportation routes should be taken into consideration. Ports, as the main component, play a significant role in connecting the whole maritime supply chain, thus providing a foundation for the importance measurement of the MCSC. This chapter analyses the importance of ports within an MCSC from a network perspective. Based on the container liner service information collected from one of the world's leading shipping companies, a maritime container transportation network (MCTN) is constructed. Both network structure measures (e.g. degree distribution, average path length and clustering coefficient) and centrality measures (e.g. degree, closeness and betweenness centrality) are applied to investigate the topological features of the liner shipping network and identify the positions of different ports in the network. Moreover, a novel indicator involving different centrality measures is proposed to assist in determining the importance of ports in maritime container transportation.

5.1 Introduction

Ports are the basic elements constituting a maritime supply chain. Thus, the study of ports in supply chain systems has been identified as a significant issue (Lam and Wei, 2011), and the importance of an MCSC within the global container logistics system can be measured and compared from a port perspective, e.g., the number of ports it contains, the relative importance of these ports, and the sequence by which the ports are connected by shipping services. Empirically, the total throughput, as one of the most available data related to port operations, has been widely applied as a principal indicator for measuring and comparing port performance both domestically and internationally (De Langen, Nijdam and Van der Horst, 2007). It is analysed together with other indices using various operation and economic modelling tools, such as data envelopment analysis and stochastic frontier analysis (Cullinane et al., 2006). However, these methods are too aggregated (Ducruet, Lee and Ng, 2010), which cannot fully reflect the relative position of seaports within maritime networks. Other quantitative studies related to the measurement of port importance, including the port selection (Steven and Corsi, 2012) and the modelling of optimal shipping routes, were mostly conducted from economic and operational aspects, without the consideration of network-specific elements.

The recent decades have witnessed great efforts on the exploration of various complex systems from a network point of view. Typical examples are communication systems (Hagen, Killinger, and Streeter, 1997), the Internet (Barabasi and Albert, 1999), social systems (Valente and Foreman, 1998), biological networks (Jeong et al., 2000), and transportation networks including airline (Barrat et al., 2004), bus (Xu, Hu and Liu, 2007), ship (Xu et al., 2007), and subway (Latora and Marchiori, 2002) networks. Despite a relatively late application and development of the network analysis in the maritime transportation field, it has rapidly gained popularity, and a number of studies have verified the rationality and practicality applying complex network analysis as a tool to deal with the relational complexity of maritime shipping networks (e.g., Ducruet, Lee and Ng, 2010; Ducruet and Notteboom, 2012; Ducruet, 2013; Calatayud, Mangan and Palacin, 2017). Bartholdi, Jarumaneeroj and Ramudhin (2016) proposed a new index for measuring the connectivity of container ports by incorporating the topological information such as the position of a port within the global shipping network. The model is able to score for both inbound and outbound container movement in order to support more detailed analysis. The study by Ducruet, Lee and Ng (2010) proved that indicators of centrality, connectivity, and vulnerability could provide more reference than that from traditional traffic statistics for defining the hierarchy of traffic volume by using network analysis in the case of Northeast Asian ports. Ducruet (2017) also investigated the multiple relations between nodes and the dynamics among the different layers of multiplex networks according to six main categories of cargo which vessels carry, that is, containers, general cargo, liquid bulks, passengers, solid bulks, and vehicles.

The development of graph theory and advanced analytical software further facilitated the analysis and visualization of networks, especially those of large scale. The literature on the application of complex network analysis in the maritime transportation area often addressed three main issues, which are 1) measurement of basic network properties, 2) analysis of complex network features and 3) identification of ports' positions within the shipping network.

Several basic indices that have been widely studied to measure the configuration of a network are degree (degree distribution), path length, clustering coefficient, diameter, and network density, etc. The relationships among these indices are also investigated as needed. These studies aim to reveal the topological properties of the sample networks or compare the difference between various types of networks. The empirical analysis of the structure of the worldwide marine transportation network (WMTN) by Deng et al. (2009) indicated that WMTN had a relatively short average path length and high clustering coefficient. In terms of the cumulative degree distribution, it followed an exponential-like distribution. Hu and Zhu (2009) comparatively studied the basic properties of the WMTN under two different representations. The results showed that cumulative degree distributions of degree under two representations were different, but the clustering coefficients both exhibited similar behaviour as functions of degree. Kaluza et al. (2010) highlighted the difference of some basic network properties among the networks of cargo movements of container ships, dry bulk carriers and oil tankers.

Some common characteristics shared by networks of many different types have been discovered including small-world effect (Watts and Strogatz, 1998), the scale-free feature (Barabasi and Albert, 1999), assortative mixing (Newman, 2002), and rich-club phenomenon (Shi and Mondragon, 2004). The investigation of these properties and laws in the global maritime transport network can help to deepen the understanding of shipping network structures. Ducruet and Notteboom (2012) evidenced the properties of scale-free and small-world in the worldwide container shipping networks constructed according to the movements of container vessels in 1996 and 2006, respectively. Similar features were also observed by Tovar, Hernández, and Rodríguez-Déniz (2015) in their study on the shipping network of Canary Islands. However, research on the WMTN by Hu and Zhu (2009) presented a truncated scale-free behaviour only in the space L and an obvious small-world property in the space P[7].

Centrality, as a fundamental concept in network analysis, has already been addressed in the maritime transportation sector as an indicator for assessing the relative importance/position of ports as early as in the 1990s (Fleming and Hayuth, 1994). In previous studies, the three most

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[7] The concept of Space L and P will be explained in Section 5.3

widely applied centrality measures in the shipping industry are degree, closeness, and betweenness centrality. Ducruet, Lee and Roussin (2009) applied betweenness centrality solely in identifying the position of South Korean ports in the Asian shipping network, and the results recognised Busan as the most central port due to its strong position for regional transhipment. In the work of Ducruet, Lee and Ng (2012), both degree and betweenness centralities were considered to measure the relative importance of Northeast Asian ports within the regional liner networks. The correlations between the two centrality measures and throughput were also checked, and the results indicated that centrality performed better reflecting the importance of hub functions compared to the conventional throughput index. Wang and Cullinane (2016) extended the application of centrality measures in a flow-movement-directed and transportation-capacity-weighted network in order to reflect better the characteristics of traffic flows in the real shipping networks. The foreland market coverage was also taken into consideration to study its influence on the port centralities.

One major limitation of the existing port centrality research is that there is little or no consideration of the difference of contributions made by different centrality measures when assessing the importance of a port in the network. This is because most previous research used only one or some of these centrality measures, or utilised all of them but with limited consideration of their different roles reflecting a port's position. As each centrality measure has its own emphasis on identifying the importance of a node, thus the application of them separately will inevitably result in the missing of information, which cannot comprehensively reflect the position of a port in the network. This chapter aims to develop a more rational and practicable measure to evaluate the importance of ports, in order to provide the basis for the overall evaluation of MCSC performance from a global perspective.

In the following, Section 5.2 outlines the methods used to measure the basic network properties and centralities and proposes a new approach for comprehensively evaluating the position of a port. The data collection, processing, and construction of the sample network are provided in Section 5.3. A case study of one world leading shipping company is used to demonstrate the application of the proposed method in Section 5.4. Section 5.5 concludes this chapter.

5.2 Methodology

Due to the fact that a highly interconnected global maritime container transportation system functions with all the features and characteristics of a typical network, it is often abstracted to a graph, in which container ports are viewed as the nodes and liner shipping services as the arcs within the network. Therefore, the MCTN provides an excellent fundamental basis for analysing its structure by using a complex network approach. In this chapter, the MCTN is abstracted as a connected network $G = (V, E)$ by V and E, where $V = \{v_i: i=1, 2,\ldots, n\}$, n is the number of nodes (ports), while $E = \{e_i: i=1, 2,\ldots, m\}$, m is the number of arcs (links between ports). To represent a network, an adjacency matrix $A_{n\times n}$ is created where an element $a_{ij} = 1$ when a container liner service exists between port v_i and v_j, and $a_{ij} = 0$ otherwise. Measures of both network structure and centrality are introduced in Section 5.2.1 and 5.2.2, respectively. Based on that, a comprehensive measure of port importance is developed and described in Section 5.2.3.

5.2.1 Measures of Network Structure

Several basic indices are studied in previous research to measure the statistical properties of a network. Among them, three most robust measures that have been widely applied in transportation research are degree distribution, average path length and clustering coefficient (Wang et al., 2011).

1) Degree and degree distribution

The degree is the number of links that a node shares with others. In an MCTN, the degree k_i represents the number of connections that port v_i has to other ports (Tovar, Hernández, and Rodríguez-Déniz, 2015). It is a simple yet intuitive indicator showing how important a node is within the cargo shipping networks. If a network is directed, then nodes have two different degrees: the in-degree, which is the number of incoming arcs; and the out-degree, which is the number of outgoing arcs. For an MCTN with n ports, if n_k of them have degree k, the degree distribution $p(k)$ is defined as the fraction of these k-degree ports, i.e., n_k /n. $P(k)$ represents the cumulative degree distribution, i.e., the fraction of ports with degrees greater than, or equal to, k, written as (Barabási and Albert, 1999):

$$P(k) = \sum_{k'=k}^{\infty} p(k') \qquad \text{Eq. 5.1}$$

In terms of physical interpretation, the degree distribution indicates the number of ports that have a certain number of shipping routes. The average degree of a network, denoted as $\langle k\rangle$, is the average number of directly connected ports that a port has in an MCTN.

2) Average path length

The distance (also known as the geodesic distance, $d(v_i, v_j)$) between two ports v_i and v_j in a graph is defined as the number of edges for the shortest path from i to j. The average path length, denoted by $\langle l \rangle$, expresses the mean length of all shortest paths in the network. Considering an unweighted directed network, it is written as (Watts and Strogatz, 1998):

$$\langle l \rangle = \frac{1}{n(n-1)} \sum_{i \neq j} d(v_i, v_j) \qquad \text{Eq. 5.2}$$

It measures the efficiency of the routes that connect any two nodes in the network. The smaller the $\langle l \rangle$ is, the more likely that the two nodes can be linked through a small number of steps. The physical interpretation of this measure corresponds to the average length of the shipping routes in an MCTN. The diameter of the network, denoted as D, is defined as the longest geodesic, i.e., the maximum value of all $d(v_i, v_j)$. It is a measure of network compactness. Thus, the lower the diameter, the more connected a network is (Tsiotas, and Polyzos, 2014).

3) Clustering coefficient

The (local) clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together. The clustering coefficient (C_i) of a node (v_i) is the portion of actual links (E_i) between the nodes within its neighbourhood divided by the maximal possible links between them. For a directed graph, there are k_i (k_i-1) links that could exist among the nodes within the neighbourhood. Thus, the clustering coefficient of a node is written as (Watts and Strogatz, 1998):

$$C_i = \frac{E_i}{k_i(k_i - 1)} \qquad \text{Eq. 5.3}$$

A large C_i value means that the node has a more compact system of connections with its neighbours. In a fully-connected network, C_i of all nodes equals 1. For an MCTN, it expresses the probability of meeting shipping connections among the neighbours of a port. The average clustering coefficient C of the whole network is the average of all C_i over all nodes, written as:

$$C = \frac{1}{n} \sum_{i=1}^{n} C_i \qquad \text{Eq. 5.4}$$

The larger the value of C is, the more likely nodes are to reach one another within a short topological distance (i.e., transhipment). It is worth noting that a network is considered to be a small-world network if its average clustering coefficient is significantly higher than a random network constructed on the same node set, and meanwhile it has a small average path length. The small-world property has been revealed in many real-world networks including Internet connectivity, electric power grids, and gene networks (Wang et al., 2011).

5.2.2 Measures of Centrality

Centrality indices were first developed in social network analysis (Newman, 2010) to study the characteristics of those crucial nodes within a graph, so that the most important ones can be identified based on their rankings. In this chapter, we adopt the three most widely applied centrality measures to investigate the importance of individual ports in an MCTN. They are degree centrality (C_D), closeness centrality (C_C), and betweenness centrality (C_B).

5.2.2.1 Degree Centrality

As the simplest centrality index, degree centrality of a node is defined as the number of links directly connected to it. It symbolises the importance of the node in a network (Freeman, 1979) based on the idea that important nodes have the largest number of links to other nodes in the network (Crucitti, Latora and Porta, 2006). Degree centrality of port v_i is defined as:

$$C_D(i) = \sum_{j=1}^{n} a_{ij} = k_i \qquad \text{Eq. 5.5}$$

where, *ki* is the degree of port v_i, and *j* represents all other ports within the MCTN. The index reflects the **connectivity** of a port in the maritime shipping network. As discussed in Section 5.2.1, two separate measures of degree centrality are further defined in the directed network, namely, in-degree ($C_{D\text{-}in}$) and out-degree centralities ($C_{D\text{-}out}$). The former represents a port's popularity, and the latter reflects its activity (Wang and Cullinane, 2016).

The degree centrality is usually normalised (which is also called the relative degree centrality) for the comparison among different networks. This can be done in a directed graph as:

$$C_D^{'}(i) = \frac{C_{D-in}(i) + C_{D-out}(i)}{2n-2} \qquad \text{Eq. 5.6}$$

where, $C_{D\text{-}in}$ (*i*) denotes the in-degree centrality of port v_i, $C_{D\text{-}out}$ (*i*) denotes the out-degree centrality of port v_i, and *n* is the number of ports within the MCTN.

5.2.2.2 Closeness Centrality

Closeness centrality measures the extent to which a node is near to all other nodes along the shortest path. It indicates how central a node is in the network. In this study, the closeness centrality of port v_i is calculated as:

$$C_C(i) = \left[\sum_{v_j \in V, i \neq j}^{n} d(v_i, v_j) \right]^{-1} \qquad \text{Eq. 5.7}$$

It can be normalised as:

$$C_C^{'}(i) = \frac{\left[\sum_{v_j \in V, i \neq j}^{n} d(v_i, v_j) \right]^{-1}}{\frac{1}{n-1}} = \frac{n-1}{\sum_{v_j \in V, i \neq j}^{n} d(v_i, v_j)} \qquad \text{Eq. 5.8}$$

The closeness centrality reflects the **accessibility** (or **reachability**) of a port, and it can be interpreted as a level of convenience that containers be shipped between this port and the others in the given MCTN. The larger the value of closeness centrality of a port, the more convenient it is to reach other port destinations within the container service network.

5.2.2.3 Betweenness Centrality

Betweenness centrality measures the extent to which a node falls between pairs of other nodes on the shortest paths connecting them in a network (Freeman, 1979). It is based on the idea that a node tends to be more powerful if it lies between many other nodes, in the sense that it works as an intermediate point controlling connections between these pairs. Thus, it is useful to measure the volume at which a port constitutes a transit station against all possible shipping routes in the MCTN. The betweenness of port v_i is defined as:

$$C_B(i) = \sum_{j \neq i \neq k \in N} \frac{\sigma_{jk}(i)}{\sigma_{jk}} \qquad \text{Eq. 5.9}$$

where, σ_{jk} denotes the sum of all shortest paths between port v_j and v_k, and $\sigma_{jk}(i)$ is the number of these shortest paths that pass through port v_i. For a directed graph, it can be normalised as (Hu and Zhu, 2009):

$$C_B^{'}(i) = \frac{1}{(n-1)(n-2)} \sum_{j \neq i \neq k \in N} \frac{\sigma_{jk}(i)}{\sigma_{jk}} \qquad \text{Eq. 5.10}$$

Betweenness centrality reflects the **transitivity** of a port. The larger the value of betweenness centrality, the more frequently a port will occur on the shortest paths between any other two ports within the MCTN.

5.2.3 Comprehensive Measurement of Port Importance

Although the above mentioned centrality measures have been widely studied and applied in the identification of important ports in maritime transportation networks, most of the studies are conducted with the consideration of only single centrality (e.g. Ducruet and Zaidi, 2012; Hu and Zhu, 2009; Laxe, Seoan and Monte, 2012). This will inevitably result in a relatively larger deviation between the computational results and the real industrial situation, as partial information provided by the single centrality cannot reflect the whole profile. In order to measure the overall impacts of a port and rank them according to the aggregated information from different centrality indices, this chapter develops a novel indicator for comprehensively scoring ports' importance, expressed as,

$$S_O(i) = w_D S_D(i) + w_C S_C(i) + w_C S_C(i) \qquad \text{Eq. 5.11}$$

where, $S_O(i)$ denotes the overall (total) score of port v_i; w_D, w_C, and w_B are the weights of score $S_D(i)$, $S_C(i)$, and $S_B(i)$, respectively, representing how much they individually contribute to the total score. w_D, w_C, and w_B are determined by the degree of correlation between normalised degree, closeness, and betweenness centralities of a port against its cargo volume, which can be calculated as,

$$\begin{gathered} w_D + w_C + w_B = 1; \\ \frac{w_D}{w_C} = \frac{r_D}{r_C}, \frac{w_D}{w_B} = \frac{r_D}{r_B}, \frac{w_C}{w_B} = \frac{r_C}{r_B} \end{gathered} \qquad \text{Eq. 5.12-1}$$

where, r_D, r_C, and r_B are correlation coefficients between normalised degree ($C'_D(i)$), closeness ($C'_C(i)$), and betweenness centralities ($C'_B(i)$) and annual container throughput (in TEU), respectively. It is noted that although container throughput cannot fully reflect the real situation of the development of a port, currently there is no other indicator that has been used as widely in the global container shipping industry to measure the performance of a port better. Thus, the container throughput is considered as a reference in this study for the calculation of weights of sores provided by different centrality measures. $S_D(i)$, $S_C(i)$, and $S_B(i)$ represent the scores obtained in terms of the normalised degree, closeness, and betweenness centralities, respectively. They are computed through the following equation.

$$\begin{aligned} S_D(i) &= n - Rank_D(i) + 1 \\ S_C(i) &= n - Rank_C(i) + 1 \\ S_B(i) &= n - Rank_B(i) + 1 \end{aligned} \qquad \text{Eq. 5.12-2}$$

where, n is the total number of ports in the network, and $Rank_D(i)$, $Rank_C(i)$, and $Rank_B(i)$ are the ranking of port v_i within the MCTN in terms of its normalised degree, closeness, and betweenness centralities, respectively. Eq. 5.12-2 is based on the idea of Borda Count Method. It is an election method in which voters rank options or candidates in order of preference. It is able to avoid the subjective bias caused by decision maker preferences, and thus provides a rational way for integrating different analysis from various centrality indices as evidenced by its implications in recent studies (e.g. Liu et al., 2018). In our case, all ports are the candidates, and the above-mentioned three centrality measures are the voters.

5.3 Construction of the Container Shipping Networks

To the best of the author's knowledge, so far there is no unanimity on how the real-life transportation system is translated into a network representation. In the container shipping industry, two topological representations originating from the research on public bus networks (Kurant and Thiran, 2006) have appeared to address this particular problem, which are space-of stops and space-of-changes representations. In the research by Ducruet, Rozenblat and Zaidi (2010), the space-of stops representation was termed as the graph of direct linkages (GDL), in which two ports would be directly linked if they are consecutive stops within a shipping route, while the space-of-changes representation was termed as the graph of all linkages (GAL), where two ports would be linked if they belong to the same liner service or loop, regardless of whether they were visited consecutively. Thus, in the GAL, indirect links are also added. In other studies, the GDL is also named space L, and the GAL is named space P (Hu and Zhu, 2009). Many studies have been conducted to compare the difference between the two network representations in terms of their basic properties and network features (e.g., Hu and Zhu, 2009; Ducruet and Notteboom, 2012; Ducruet and Zaidi, 2012).

Generally, a container's journey seldom exactly aligns with the start and end of one service due to the influencing factors such as today's hub-and-spoke design, and the emergence of transhipment (Viljoen and Joubert, 2016). Moreover, from a perspective of cargo movement, the GAL is expected to be a better representation of liner shipping as in the real-life situation it is possible for a container to be transported to any port from the departure port within the same shipping route. Therefore, this study adopts GAL to build the container shipping network, that is, all ports in the same service are considered linked either directly or indirectly.

5.3.1 Data Collection and Processing

Previous studies revealed that the data used for network analysis is normally obtained from two major sources: shipping service information from individual liners' official websites or published in Containerisation International Yearbooks; the automatic identification system (AIS) information of actual ship movements collected online or recorded by Lloyd's Maritime Intelligence Unit. The example chosen for illustration in this chapter is a world leading carrier - COSCO SHIPPING Lines Co., Ltd. The maritime data was sourced from the service information of COSCO published online (http://lines.coscoshipping.com/home/). The schedule information from 6th March to 7th May in 2017 was collected, and basic information of a specific route includes ports of call (port rotation), time schedule, ship fleet, and ship capacity. A time span of two months is considered in this study as this time period can cover the longest time a voyage may take. By applying a GAL representation, each shipping route can be interpreted as a small network where all ports in the same shipping route are linked together, and the merging of all these individual sub-networks results in the complete network.

This kind of dataset based on individual liner shipping companies is justified because available studies (Kivelä et al., 2013; Ducruet, 2017) revealed that the global container shipping network could be regarded as a multi-layered structure resulting from the aggregation of container shipping networks provided by different container shipping lines, and it has already been widely accepted as the basis for analysis of, for instance, relationships and dynamics between ports (Ducruet, 2013), centrality of shipping areas (Liu, Xu and Shi, 2015), and port centrality in maritime container transportation (Wang and Cullinane, 2016). However, as this study mainly focuses on developing new approaches for the rational measurement of the importance of ports in the maritime shipping network, service information from only one shipping company is collected for a demonstration purpose. It is important to highlight that, unlike other previous research, such as Ducruet and Zaidi (2012) and Tovar, Hernández, and Rodríguez-Déniz (2015), among others, the direction of cargo flow movements is considered in this study, which is of great significance to reflect the phenomena of trade imbalance existing in the global trade. Besides, the real maritime transportation networks should be directed and asymmetric due to the existence of circular routes (Hu and Zhu, 2009).

One limitation the dataset might face is that the links between all pairs of ports within the sample network are treated with the same weight due to the lack of availability of actual container traffic statistics (the container shipping companies' statistical data on traffic flows handled by each pair of ports is supposed to be highly strategic for competition, and this kind of data is usually confidential).

5.3.2 Description of the Sample Shipping Network

Based on shipping practices and shipping schedules of the shipping company under investigation, six main trade lanes are categorised in this research. They are Trans-Pacific Trade Lane, Europe Trade Lane, Europe Feeder & Trans-Atlantic Trade Lane, Asian Pacific Trade Lane, Latin America&/Africa Trade Lane, and Southeast & South Asia Trade Lane. Each trade lane connects certain regions, and specific routes are designed to serve shipping demand between these regions. The combination of numerous routes forms the network.

Based on the information of 123 shipping routes in the dataset, an unweighted and directed network is constructed composing of 212 nodes and 3425 arcs. The distribution of these ports is listed in Table 5.1

Table 5.1. Port distributions

Shipping area		No. of countries	No. of ports	% of total port No.
Asia	Northeast Asia	3	36	17.0%
	Southeast Asia	7	14	6.6%
	South Asia	3	8	3.8%
	West Asia	10	25	11.8%
America	North America	8	30	14.2%
	South America	7	19	8.9%
Africa		16	28	13.2%
Europe		20	41	19.3%
Oceania		2	11	5.2%

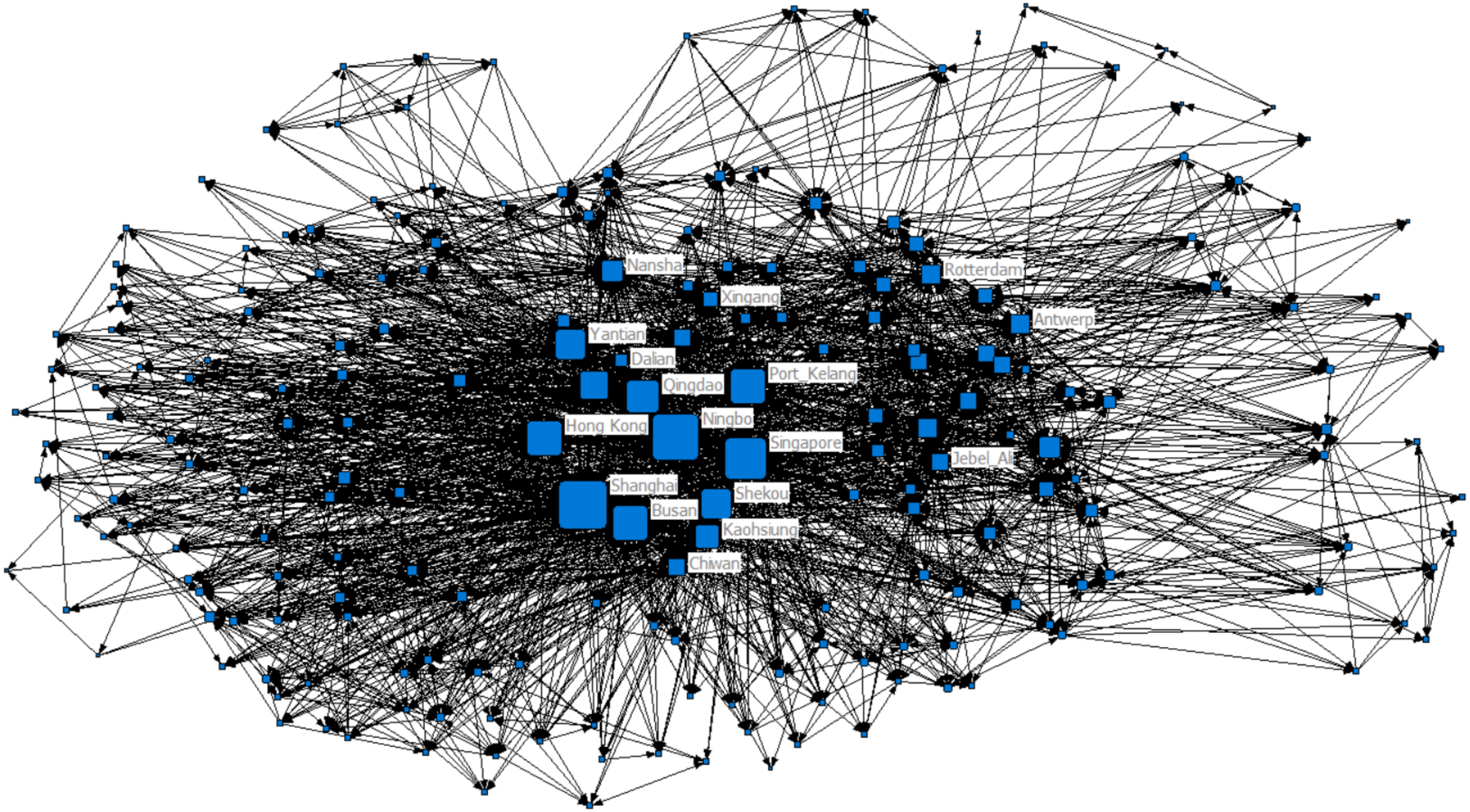


Figure 5.1. Graph of the sample network

Source: realised by the author based on COSCO service data and NetDraw software. Node's size according to degree centrality (for better readability, only the names of the top 15 ports in terms of their throughputs in 2016 are presented)

In terms of the sample network based on the information collected from COSCO, the Asia area holds the highest number of countries, followed by the area of Europe with 20 countries. Meanwhile, Asian countries contribute the most in terms of the number of ports in the network, accounting for 39.2% of the total number. Although there are only three countries under consideration in the Northeast Asia area- China, Japan, and South Korea- 26 out of the 36 ports belong to China, taking up 12.3% of the total number. China is the country that contributes the most to the network in terms of the port number. The other three countries with at least ten ports being involved are the USA, Turkey, and Italy. This is to some extent in accordance with their total volume of import and export trade (CIA, 2017), and it is also part of the reflection of the shipping company's marketing strategy. A graph representation of the sample network is shown in Figure 5.1.

5.4 Empirical Application and Analysis

By the end of February 2018, COSCO had a total of 343 container ships (including 53 ships with a capacity equal to or above 10,000 TEUs), with a total carrying capacity of 1.86 million TEUs (8.5 per cent of the world total container shipping capacity), ranking the fourth place in the world (first place in China) for the scale of the container fleet (Alphaliner, 2018). Thus, we believe that COSCO is a suitable selection for the case study of the maritime network analysis considering both the representative role in shipping companies worldwide and the convenience of data collection. Within the context of this study, the sample MCTN consists of 212 container ports from 76 countries. This section aims to show the characteristics of the sample shipping network and demonstrate the applicability of the proposed methods on the measurement of ports’ importance.

5.4.1 Statistical Properties of the Sample MCTN

1) Degree and degree distribution

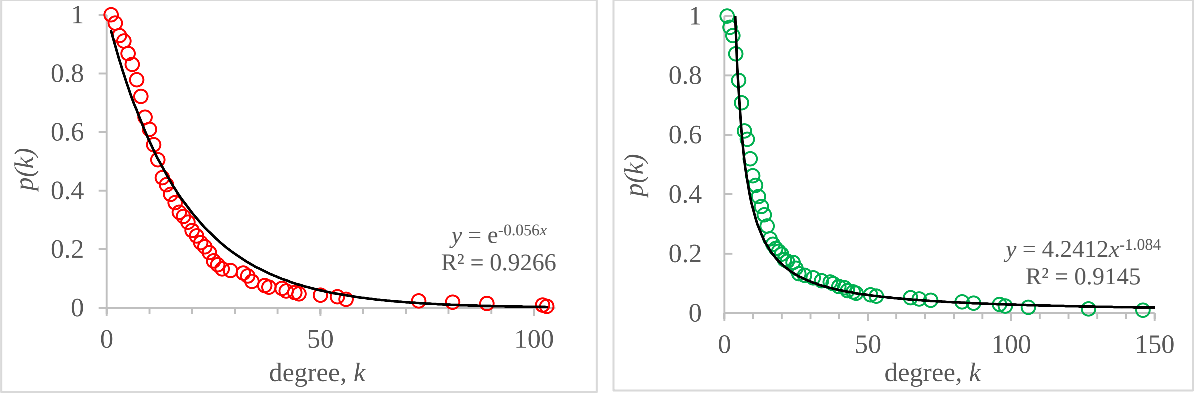
The ports with a relatively high number of connections (with a degree of 40 at least) in the sample network in terms of their in-degree and out-degree are listed in Table 5.2. It can be seen that Singapore, Port Klang (Malaysia), and Shanghai are the three most popular ports as more ports tend to connect to them, while the top three active ports are recognised as Shanghai, Ningbo, and Singapore, due to the large number of outgoing shipping routes they possess. Most of these ports are in Asia (except for Piraeus and Rotterdam), and their roles as a transport hub can be classified into two main types: either as a gateway hub (e.g., Shanghai, Ningbo, and

Rotterdam) which is crucial in connecting the inland and overseas market or as a transhipment hub (e.g., Singapore, and Busan) being able to attract a large number of cargos from neighbouring ports owing to their superior geographical locations for transhipment.

Table 5.2. List of most connected ports ($k \geq 40$)

Port	In-degree	Rank	Port	Out-degree	Rank
Singapore	103	1	Shanghai	152	1
Port Klang*	102	2	Ningbo	146	2
Shanghai	89	3	Singapore	127	3
Hong Kong	81	4	Busan	106	4
Qingdao	73	5	Qingdao	98	5
Busan	56	6	Hong Kong	96	6
Piraeus	54	7	Shekou**	87	7
Jeddah	54	8	Yantian**	83	8
Rotterdam	50	9	Kaohsiung	72	9
Xiamen	45	10	Xiamen	68	10
Khor Fakkan	44	11	Port Klang*	65	11
Kaohsiung	42	12	Nansha	53	12
Yantian**	41	13	Piraeus	51	13
Colombo	41	14	Jebel Ali	46	14
* It refers to Port Klang north and south combined. ** They all belong to Shenzhen Port. *** It refers to the Tianjin-Xingang Port.			Rotterdam	45	15
			Antwerp	43	16
			Xingang***	42	17
			Chiwan**	42	18
			Nhava Sheva	40	19

In order to reduce the statistical errors arising from the limited sample size, we use the cumulative distribution to describe the in-degree and out-degree of ports. The cumulative degree distributions are shown in Figure 5.2.



(*a*) (*b*)

Figure 5.2. Cumulative degree distributions of degree. (a) In-degree distribution. (b) Out-degree distribution. Source: realised by authors based on the COSCO data

The out-degree distribution follows a power-law distribution, and it can be described by the power law $p(k_{out}) \sim k^{-r}$ with r =1.084. While, the in-degree can be approximated by an exponential function as $p(k_{in}) = e^{-0.056k}$ with a vertical intercept of 1. They both signify that a few main ports at the top dominate the network with a large number of shipping routes, and the number of routes to each port declines quickly and levels off towards small ports. For example, the top 20% of ports account for a majority (55%) of all shipping routes, and numerous ports (around half of the total) at the bottom have only a limited number of connections (less than 10). The cumulative distributions of degree approximately follow the Pareto principle, that is, about 80% of the effects come from 20% of the causes. The power-law distribution of out-degree is similar to the case of the Northeast Asian liner network in 2006 (Ducruet, Lee, and Ng, 2010), while the exponential properties of in-degree distribution are more consistent with that of the worldwide maritime transportation network case studied by Hu and Zhu (2009). They also revealed that the cumulative degree distributions of degree in a GAL representation are different from that in a GDL representation. Regarding the fitting curves, the high coefficients of determination ($R^2 > 0.9$) in Figure 5.2 indicate that both models can almost perfectly describe the variation of the distribution of in-degree and out-degree data.

2) Average path length

The average path length reflects the convenience of transportation of cargos in the sample network. Based on Eq. 5.2, the average path length of the sample network can be calculated as $\langle l \rangle = 2.28$. This generally means, in the world shipping service network of COSCO, it takes over one transhipment on average to deliver the container to any destination port. This number is slightly larger than a random network ($\langle l_r \rangle \approx 1.93$) of the same scale. The diameter of the sample network is 5 (at least four transhipments), which exists in connections between the Port of Ravenna (Italy) and the Port of Humen (China). The average path length of 2.28 in the sample network is very similar to that of the global container shipping network (2.26) established also based on a GAL representation by Ducruet and Notteboom (2012). It is noted that the network of GAL representation is generally more efficient than that of GDL representation because the inclusion of indirect links facilitates the circulation of flows in the network, as reflected by its shorter average path length.

3) Clustering coefficient

Clustering coefficient is used as an indicator to reflect the local cohesiveness of the network in the neighbourhood of the node. The sample network's clustering coefficient is 0.62, much larger than that for a random network ($C_r \approx 0.076$) of the same size. A larger clustering coefficient confirms the high-degree of concentration identified earlier and also implies a high probability for containers being transported to the destination with fewer transhipments in the network. With a high clustering coefficient (0.62) as well as a small average shortest path length (2.28) of the sample network, we conclude that the MCTN of COSCO has a small-world property as shown in other maritime shipping networks (e.g., Hu and Zhu, 2009; Ducruet and Notteboom, 2012; Zong and Hu, 2017). A comparison of the statistical properties between the sample network in this chapter and that of other maritime transportation network cases is summarised in Table 5.3.

The comparison shows that, despite the fundamental differences in size and structure, these networks share similar features such as the close average path length, relative high clustering coefficient, and an apparent small-world phenomenon, indicating the rationality of the data, and the representative role of the sample network in this study evidenced by the similar topological features compared with other global maritime shipping networks. Thus, the sample network also can be treated as a kind of complex network, and the centrality measures will be applied to the port-related analysis in the following section.

Table 5.3. Comparison of characteristics of different networks

Author	**Type of network**	***n***	***m***	$\langle k \rangle$	$\langle l \rangle$	***C***	**Network structure**
Xu et al. (2007)*	Ship-transport network of China	162	61060	8.27	3.87	0.83	Truncated SF; SW**
Hu and Zhu (2009)*	Worldwide maritime transportation network	878	24967	28.44	2.66	0.71	SW
Kaluza et al. (2010)	Network of global container ships	378	-	32.4	2.76	0.52	SW
Ducruet and Notteboom (2012)*	Global container shipping network	1205	51057	87.52	2.22	0.73	SF; SW
In this chapter	Global container shipping network of COSCO	212	3425	16.16	2.28	0.62	SW

* Although statistical properties of the networks in both GDL and GAL were investigated by the authors, we only focus on the comparison of GAL results.

** SF denotes scale-free, and SW refers to the small-world network.

5.4.2 Centralities of Ports in the MCTN

In order to identify the relative positions of container ports within the shipping network, port centralities have been examined from the perspective of their direct connectivity (degree centrality), reachability to other ports (closeness centrality), and transitive position on other pairs of ports (closeness centrality). Computational results of all ports are listed in Appendix Seven.

1) Degree centrality

Degree centrality is a local level measure indicating the number of direct connections linking the port with others. Based on Eq. 5.5 and 5.6, normalised degree centralities of all ports can be obtained, and the top 20 are listed in Table 5.4. Among them, 16 out of 20 are Asian ports (ten of them are Chinese ports), and the other four are European ports (i.e., Piraeus, Rotterdam, Antwerp, and Hamburg)

Table 5.4. Top 20 ports in terms of normalised degree centrality

Rank	**Port**	$\mathbf{C}'_{\boldsymbol{D}}(\boldsymbol{i})$	**Rank**	**Port**	$\mathbf{C}'_{\boldsymbol{D}}(\boldsymbol{i})$
1	Shanghai	0.5711	11	Xiamen	0.2678
2	Singapore	0.5450	12	Piraeus	0.2488
3	Ningbo	0.4265	13	Rotterdam	0.2251
4	Hong Kong	0.4194	14	Jeddah	0.2180
5	Qingdao	0.4052	15	Nansha	0.2156
6	Port Klang	0.3957	16	Jebel Ali	0.1967
7	Busan	0.3839	17	Antwerp	0.1825
8	Yantian	0.2938	18	Hamburg	0.1706
9	Shekou	0.2844	19	Colombo	0.1706
10	Kaohsiung	0.2701	20	Xingang	0.1635

In terms of the situation in the whole network, there are only two ports (Shanghai and Singapore) that have a relative degree centrality value more than 0.5, which means that they are directly connected to more than half of the ports in the sample network, revealing their strategic positions with respect to the service offered by COSCO. The total number of ports with a relative degree centrality above 0.1 is 40 (apart from Shanghai and Singapore, it consists of 25 ports between 0.1 and 0.2; 8 ports between 0.2 and 0.3; 2 ports between 0.3 and 0.4, and 3 ports between 0.4 and 0.5), accounting for 18.87% of the total number of ports in the sample network. The remaining 172 ports are less connected with a relative degree centrality below 0.1. Geographical distribution of the most connected ports (with a relative degree centrality above 0.2) is shown in Figure 5.3.

Figure 5.3. Ports with a degree centrality above 0.2

2) Closeness centrality

Closeness centrality is a global level measure relating to the distance of a port to all others in the network. Based on Eq. 5.7 and 5.8, normalised closeness centralities of all ports can be obtained, and the top 20 are listed in Table 5.5. Shanghai, Ningbo, and Singapore are still among the top three places. However, Ningbo surpasses Singapore in terms of the relative value of closeness centrality, ranking the second. This means that Ningbo locates in a more central position compared to Singapore in the sample network, though it has relatively fewer direct connections with neighbouring ports.

Table 5.5. Top 20 ports in terms of normalised closeness centrality

Rank	**Port**	$C'_C(i)$	**Rank**	**Port**	$C'_C(i)$
1	Shanghai	0.8023	11	Kaohsiung	0.6063
2	Ningbo	0.7701	12	Nansha	0.5960
3	Singapore	0.7456	13	Piraeus	0.5910
4	Hong Kong	0.6873	14	Jeddah	0.5813
5	Busan	0.6785	15	Rotterdam	0.5765
6	Port Klang	0.6763	16	Antwerp	0.5734
7	Qingdao	0.6573	17	Colombo	0.5672
8	Yantian	0.6394	18	Hamburg	0.5672
9	Shekou	0.6394	19	Khor Fakkan	0.5642
10	Xiamen	0.6280	20	Jebel Ali	0.5642

In terms of the situation in the whole network, Shanghai is the only one that has a relative closeness centrality value of more than 0.8, showing its most central position in the network. The total number of ports with a relative closeness centrality above 0.5 is 61 (apart from

Shanghai, it consists of 50 ports between 0.5 and 0.6, 8 ports between 0.6 and 0.7, and 2 ports between 0.7 and 0.8), accounting for 28.77% of the total number of ports in the sample network. A relative closeness centrality value higher than 0.5 indicates that container transportation between these pairs of ports can be achieved directly or depending on one other intermediary port. Geographical distribution of those most central ports (with a relative closeness centrality equal to or above 0.5) is shown in Figure 5.4.

Figure 5.4. Ports with a closeness centrality above (or equal to) 0.5

3) Betweenness centrality

As another global level measure, betweenness centrality indicates the potential of ports to be utilized as an intermediate transhipment station for completing the delivery of containers between pairs of ports. Based on Eq. 5.9 and 5.10, normalised betweenness centralities of all ports can be obtained, and the top 20 are listed in Table 5.6. Singapore ranks the first in terms of betweenness centrality, surpassing Shanghai for the first time. It reflects the difference of this indicator when identifying important ports, which emphasizes more on the transhipment function on a port. This can be evidenced by the improved performance of Busan and Rotterdam in terms of betweenness centrality, which play the important role of regional transhipment centre in the Northeast Asia area and Western Europe area, respectively.

Table 5.6. Top 20 ports in terms of normalised betweenness centrality

Rank	**Port**	$C'_B(i)$	**Rank**	**Port**	$C'_B(i)$
1	Singapore	0.1608	11	Xiamen	0.0312
2	Shanghai	0.1560	12	Kaohsiung	0.0267
3	Hong Kong	0.0794	13	Piraeus	0.0242
4	Busan	0.0728	14	Fangchenggang	0.0235
5	Qingdao	0.0699	15	Felixstowe	0.0196
6	Port Klang	0.0693	16	Genoa	0.0185
7	Rotterdam	0.0615	17	Jeddah	0.0180
8	Yantian	0.0458	18	Shekou	0.0176
9	Ningbo	0.0349	19	Jebel Ali	0.0137
10	Nansha	0.0317	20	Algeciras	0.0108

In terms of the situation in the whole network, there are only 20 ports which have a relative betweenness centrality value more than 0.01 (it consists of 9 ports between 0.01 and 0.03, 4 ports between 0.03 and 0.06, 5 ports between 0.06 and 0.1, and 2 ports above 0.1), accounting for 9.43% of the total number of ports in the sample network. Normalised betweenness centrality values of all ports are relatively low compared to the values of the other two centrality measures, which reveals that the "control" effects of these ports being identified as transhipment hubs are still limited to a regional level rather than global level. Geographical distribution of those ports (with a relative betweenness centrality above 0.01) is shown in Figure 5.5.

Figure 5.5. Ports with a betweenness centrality above 0.01

The top 20 ports with respect to different centrality measures are summarised in Table 5.7. It can be seen that the ranking of ports varies according to the different indicators. However, some ports maintain relatively high importance and their names appear in the ranking list repeatedly, such as Shanghai, Singapore, Ningbo, Hong Kong, Busan, to name just a few.

Table 5.7. Top 20 ports by normalised degree, closeness, and betweenness.

Rank	Degree	Closeness	Betweenness	Rank	Degree	Closeness	Betweenness
1	Shanghai	Shanghai	Singapore	11	Xiamen	Kaohsiung	Xiamen
2	Singapore	Ningbo	Shanghai	12	Piraeus	Nansha	Kaohsiung
3	Ningbo	Singapore	Hong Kong	13	Rotterdam	Piraeus	Piraeus
4	Hong Kong	Hong Kong	Busan	14	Jeddah	Jeddah	Fangchenggang
5	Qingdao	Busan	Qingdao	15	Nansha	Rotterdam	Felixstowe
6	Port Klang	Port Klang	Port Klang	16	Jebel Ali	Antwerp	Genoa
7	Busan	Qingdao	Rotterdam	17	Antwerp	Colombo	Jeddah
8	Yantian	Yantian	Yantian	18	Colombo	Hamburg	Shekou
9	Shekou	Shekou	Ningbo	19	Hamburg	Khor Fakkan	Jebel Ali
10	Kaohsiung	Xiamen	Nansha	20	Xingang	Jebel Ali	Algeciras

Source: Own elaboration based on Appendix Seven.

5.4.3 Measuring the Overall Importance of Ports

This section comprehensively estimates the importance of each port considering both its topological features in the network and its real development situation in the global shipping industry. According to the statistics report by Lloyd's List (2017), the top 20 busiest ports in terms of their container throughput are listed in Table 5.8. The throughput of the top 20 ports contributes to 57.4% of the total world throughput in 2016.

Table 5.8. The world's 20 busiest container ports in 2016

Rank	Port	Country	Throughput (million TEU)
1	Shanghai	China	36.54
2	Singapore	Singapore	30.92
3	Shenzhen	China	24.20
4	Ningbo-Zhoushan	China	20.62
5	Hong Kong	S.A.R., China	20.11
6	Busan	South Korea	19.47
7	Guangzhou	China	17.62
8	Qingdao	China	17.51
9	Dubai	United Arab Emirates	15.59
10	Tianjin	China	14.10
11	Rotterdam	Netherlands	12.24
12	Port Klang	Malaysia	11.89
13	Kaohsiung	Taiwan, China	10.26
14	Antwerp	Belgium	9.65
15	Dalian	China	9.45
16	Xiamen	China	9.18
17	Tanjung Pelepas	Malaysia	9.12
18	Hamburg	Germany	8.82
19	Los Angeles	The U.S.A.	8.16
20	Long Beach	The U.S.A.	7.19

Source: Lloyd's List [8]

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[8] https://lloydslist.maritimeintelligence.informa.com/one-hundred-container-ports-2016?pg=1

Due to the relative stability of the scheduled service network of a container shipping company during a certain period of time, the data collected from March 2017 basically reflects the development of world container shipping industry in the year of 2016. Thus, the correlation coefficients between the throughput of the port and its degree, closeness, and betweenness centralities are calculated respectively. The results show that $r_D = 0.832$, $r_C = 0.822$, and $r_B = 0.862$ (correlations between port throughputs and degree, closeness, and betweenness centrality values are depicted in Figure 5.6, 5.7, and 5.8, respectively). Based on Eq. 5.12-1, the weights of each centrality measure can be computed, which are $w_D = 0.331$, $w_C = 0.326$, and $w_B = 0.343$.

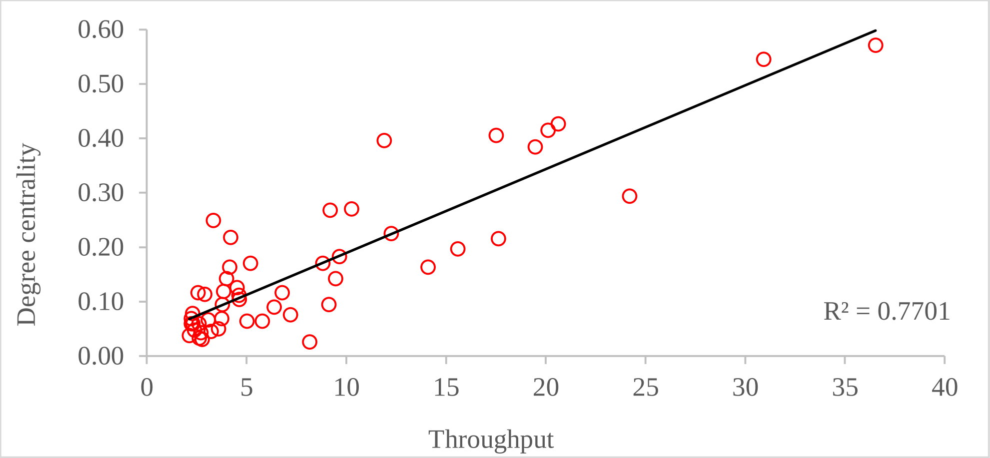


Figure 5.6. Correlations between port throughputs and degree centralities

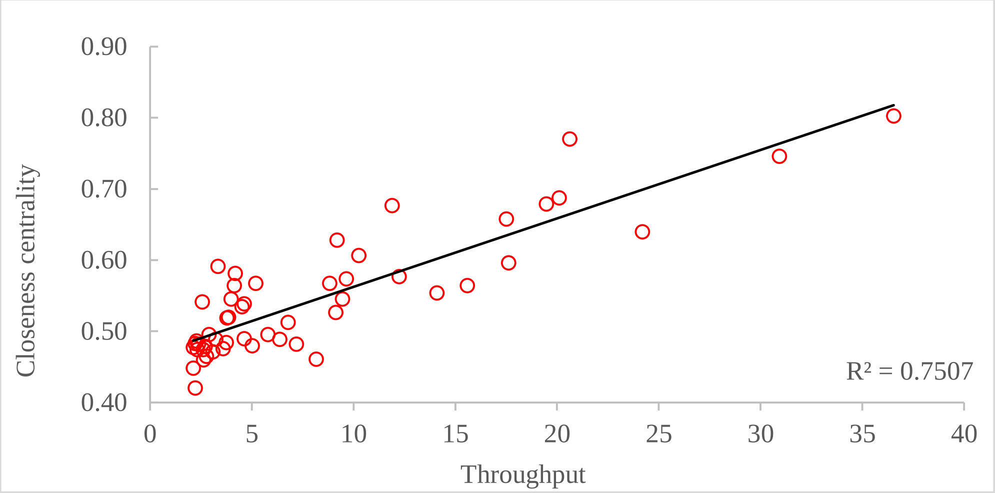


Figure 5.7. Correlations between port throughputs and closeness centralities

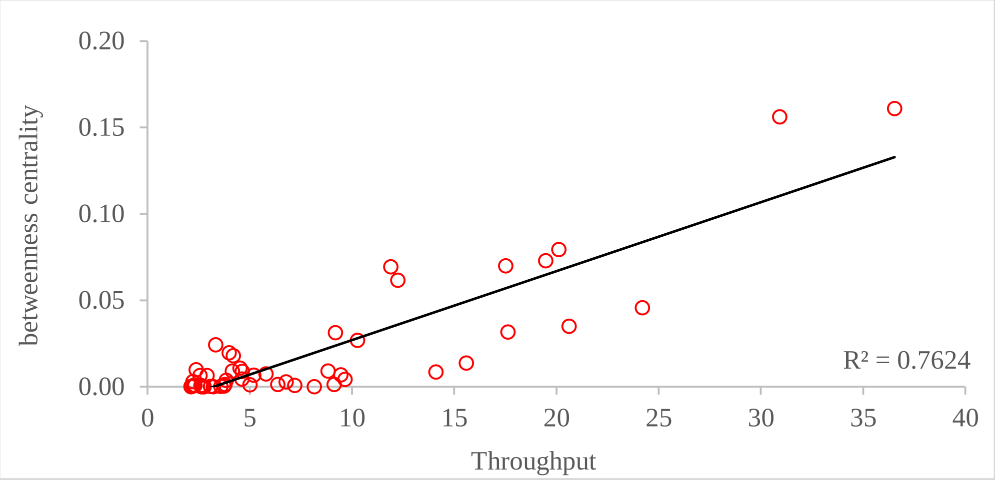


Figure 5.8. Correlations between port throughputs and betweenness centralities

The scores of each port in terms of degree, closeness, and betweenness centralities are developed based on the Borda Count method using Eq. 5.12-2. For example, there are altogether 212 ports in the sample network, and the normalised degree centrality of Hong Kong ranks fourth, so it gets the point of $S_D = 209$; the normalised closeness centrality of this port also ranks fourth, and it gets $S_C = 209$; the normalised betweenness centrality of this port ranks third, so it has $S_B = 210$ points. Then, the total score of Hong Kong can be calculated as the following using Eq. 5.11,

$$S_O(Hong\ Kong) = 0.331 \times 209 + 0.326 \times 209 + 0.343 \times 210 = 209.343$$

Similarly, overall scores of all ports are calculated and ranked. Based on the results, the top 20 ports are shown in Table 5.9.

Table 5.9. Ranking of top 20 most important ports in terms of their overall scores

Rank	Port	$\boldsymbol{S_O(i)}$	Rank	Port	$\boldsymbol{S_O(i)}$
1	Shanghai	211.657	11	Rotterdam	201.406
2	Singapore	211.017	12	Shekou	201.239
3	Hong Kong	209.343	13	Nansha	200.693
4	Ningbo	208.268	14	Piraeus	200.331
5	Busan	207.681	15	Jeddah	197.971
6	Qingdao	207.348	16	Jebel Ali	194.993
7	Port Klang	207	17	Hamburg	192.925
8	Yantian	205	18	Khor Fakkan	191.954
9	Xiamen	202.326	19	Felixstowe	191.761
10	Kaohsiung	201.988	20	Genoa	191.097

By comparing the results of Table 5.8 and 5.9, we can find that 15 out of the 20 ports are shown in both tables, which reveals a certain degree of consistency of both methods in identifying the important ports. However, the proposed indicator, as a combination of centrality measures and port throughput, is able to provide more comprehensive information of a port's position in the shipping network than that provided by either centrality indexes or operational indexes.

5.5 Conclusion

As the global maritime transportation network can be treated as a combination of individual liner shipping companies' service networks, the vulnerability of such multiplex shipping networks can be explored from a local company's level. Given that use of single centrality is arguable to provide sufficient information about vulnerability analysis of ports for rational decision making, this chapter proposes a novel multi-centrality indicator hybridizing degree centrality, closeness centrality, and betweenness centrality, for comprehensively evaluating the importance of a port considering both its topological features within the network and its development situation. This can provide insights on the identification of vulnerability in maritime supply networks, and the proposed method can be applied in the shipping networks of other companies. The research results in this chapter will also provide the basis for the analysis of MCSC performance from a global perspective.

CHAPTER 6 - AN INTEGRATED APPROACH FOR RESILIENCE ANALYSIS OF MCSCS FROM A SYSTEMATIC PERSPECTIVE

Summary

Analysis of individual risk factors is unable to reveal the overall operational status of the whole MCSC, which only provides a limited reference for managers on daily risk management. Uncertainties existing in the complex supply chain environment and the lack of statistical data make the risk management and decision-making more difficult. In light of this, this chapter, for the first time, develops an integrated framework to facilitate a more comprehensive evaluation of MCSC performance by taking into consideration both local risk factor estimations and their global impacts on the vulnerability of the whole supply network. This is achieved by incorporating the risk matrix, the BR-BN method, and network centralities with the evidential reasoning (ER) approach in a complementary manner. The BR-BN (Chapter 4) provides a flexible and informative method to transform input information of risk parameters into risk evaluations of individual risk factors, while the *ARI* values obtained from risk matrix (Chapter 3) and the overall importance scores of ports calculated according to centrality measures (Chapter 5) provide a basis to determine the weight of each risk factor within a single MCSC, and that of each MCSC in a container shipping supply network, respectively. Finally, the ER algorithm is used to aggregate the estimations of risk factors and risk condition of MCSCs collectively, so as to support a dynamic risk-based resilience impact analysis in maritime container shipping from a systematic perspective.

6.1 Introduction

There have been a number of studies addressing the maritime safety issues from different perspectives. For example, Zhan, Xu, and Zhang (2009) applied Hazards and Operability analysis (HAZOP) to assess the risks of 10,000 TEU container ships. In the research, the risk sources of container ships were classified into three categories, which are marine-related risks (e.g. boilers, generators, and pressure vessel), navigation-related risks (e.g. lifeboat operation, dangerous goods, and piracy), and deck activity-related risks (e.g. welding, grinding, and hoist operation). These risk factors were analysed in terms of their probability of occurrence, the severity of the consequence, and the risk rating. In another research on container ships, Kim et al. (2013) focused on the hull girder collapse caused by grounding accidents mainly with respect to four types of containerships, namely, 3500TEU, 5000TEU, 7500TEU and 13,000TEU, in order to develop proper safety guidelines for container ships under such accidents. For another example, Alyami et al. (2014) identified 24 significant hazards of container terminal operations and ranked them according to a newly proposed index calculated based on the failure occurrence likelihood, consequence severity, probability of failures being undetected, and impact of a failure on the resilience of port operational systems. Other research perspectives include technological factors related to ships (Matsumoto, Miyake, and Harada, 2013; Cui, Wang and Ma, 2017), human factors (Chauvin et al., 2013; Soner, Asan and Celik, 2015), port operations (Alyami et al., 2016; Wan et al., 2017), and navigation environment (Yan et al., 2017). However, most of the previous studies concentrated on one single aspect when assessing the MCSC risks. To extend the research of risk analysis in container shipping operations, Chang, Xu and Song (2015) provided an overview of all the potential risks emerging from the information flow, the physical flow, and the finance flow. Still, the research only dealt with the operational risk in container maritime shipping without the consideration of other aspects of a complete MCSC. Moreover, the identified risk factors were usually analysed from a local perspective, which cannot reveal the global risk condition of MCSCs, let alone their impacts on the resilience of the whole shipping network. Therefore, a more systematic and inclusive way is in urgent need in order to comprehensively evaluate the overall situation of an MCSC considering risk factors from both engineering (or technical) and managerial aspects.

Regarding the resilience analysis of a maritime transportation network, one most commonly used method is to compare the variation of certain indexes related to the network performance before and after the removal of some nodes/links (Zhao et al., 2011; Azad et al., 2014; Kim, Chen and Linderman, 2015; Zhen et al., 2016). These indexes can be generally classified into two categories, which reflect either the relative drop of network performance (including network average degree, clustering coefficient, average short path length, and network efficiency) (Wang et al., 2016), or the relative increase of cost/time of a logistics process (Scott et al., 2006). In the maritime container shipping industry, the removal of a node implies the shutdown of an entire port, and the removal of a link can be regarded as the changing of service configurations of a shipping company (Viljoen and Joubert, 2016). Practically, disruptions of a supply chain are initially divided into random disruptions and targeted ones. Random disruptions imply the removal of the components (nodes or links) of a supply network in a random manner, which may be caused by, for example, natural disasters (such as hurricane and earthquake) and unexpected accidents (such as the explosion that temporarily shut down two container terminals at the port of Tianjin, China (Wan et al., 2018). While targeted disruptions (e.g., deliberate attack) will prioritise the removal of the components following a special strategy such as node degree, link betweenness, and link salience (Viljoen and Joubert, 2016), in order to cause the maximal damage (Crucitti, 2000). However, both random and targeted disruptions cannot reflect the real situation in practice, which can be regarded as two kinds of extremes. In practice, the disruption of an MCSC is neither totally random nor targeted. Instead, it is a situation between them as the occurrence of disruption is closely related to the risk condition of an MCSC. In other words, a disruption is more likely to occur in the supply chain with higher risk level. However, it is worth noting that a higher likelihood of disruption of a supply chain does not necessarily mean a higher impact on the supply network resilience, as the impact of disruption also depends on the specific role a supply chain plays in the whole system.

Therefore, this chapter tries to propose an integrated framework enabling evaluation of not only the individual risk factors within an MCSC but also the risk condition of the MCSC and its impact on the resilience of the whole logistics system in order to generate a full risk map of the global container supply network. To achieve the above aims, this chapter is structured as follows. Section 6.2 briefly reviews the models and methods involved in the proposed framework. Based on that, Section 6.3 explains in detail how to carry out the evaluation of MCSC performance step by step. The reasonability and practicality of the proposed framework are validated in Section 6.4 by using the case of a world-leading container shipping company. This chapter is concluded in Section 6.5.

6.2 Background Information

The integrated approach proposed in this chapter is developed based on a series of models and techniques used in the risk management of maritime supply chains, including risk matrices, fuzzy brief rules, BNs, centrality analysis, and the evidential reasoning (ER) approach. The risk matrix method, fuzzy logic, and BNs have been introduced in Section 2.3.2. In the proposed framework of this chapter, the risk matrix is used to determine the relative importance of each identified risk factor in MCSCs according to their *ARI* values. This will support the synthesis of risk factors in the assessment of the risk condition of the MCSC. Refer to Chapter

3 for detailed information on how to calculate the *ARI* of each risk factor. Regarding the centralities of ports obtained in Chapter 5, they will be used in the proposed framework to assist in calculating the importance of MCSCs. Refer to Chapter 5 for more information on the calculations and applications of different centrality measures in the maritime industry.

Introduction and application of other methods involved in the integrated framework are presented in the following subsections.

6.2.1 Belief rule-based Bayesian network approach

In 2008, Yang, Bonsall and Wang (2008) proposed a novel and advanced risk analysis method by incorporating the fuzzy logic, belief rule base (BRB), and Bayesian reasoning mechanism into the traditional failure mode and effects analysis (FMEA) for efficiently prioritizing failures, which is named fuzzy rule-based Bayesian reasoning approach (FuRBaR). Compared to the traditional risk assessment methods, the proposed approach shows some superiorities such as the flexibility of using human knowledge, the ability to deal with uncertainties in the information, and improved accuracy of risk analysis results. Necessary steps required for applying the FuRBaR approach to the risk assessment includes (Yang, Bonsall and Wang, 2008):

1) Establishment of fuzzy BRB within FMEA;
2) Failure estimation and transformation;
3) Rule aggregation using a Bayesian reasoning mechanism;
4) Development of utility functions for failure ranking.

Many new applications of the approach (or similar) have been seen in different research fields. For example, Hu et al. (2011) applied the approach to pipeline leak detection and leak size estimation. Yang et al. (2013) adopted the FuRBaR approach to improving the traditional cognitive reliability and error analysis method (CREAM) in order to facilitate human reliability analysis in the maritime context. Besides, there are also studies trying to improve the FuRBaR approach by dealing with some of its limitations. Alyami et al. (2014) proposed a proportion method to rationalise belief degree distributions in the BRB and simplify the communication between risk input and output, in order to facilitate its implementation in practice. In Chapter 4, the BR-BN method was further improved from two main aspects: a) the incorporation of new risk parameters in order to support more comprehensive and accurate risk analysis, and b) the consideration of the weight of each risk parameter which allows for a more sound and rational belief degree distribution.

This chapter applies the BR-BN approach to evaluate the selected risk factors within MCSCs in detail from a local perspective. Refer to Chapter 4 for further information on the procedures to carry out the BR-BN approach.

6.2.2 Evidential Reasoning Approach

The ER algorithm was developed in the 1990s based on the evidence combination rule of the D-S theory and decision theory (Yang and Singh, 1994) in order to support solutions of multiple attribute decision making (MADM) problems under uncertainties. After that, it has been further developed and improved towards a more rational and pragmatic way by extensive research, such as the proposal of the utility-based information transformation techniques within the ER framework (Yang, 2001), modification of the ER algorithm with respect to the treatment of the unassigned belief degree (Yang and Xu, 2002), the combination with the fuzzy theory (Yang et al., 2006), design and application of the multi-criteria decision analysis tool - intelligent decision system (IDS) - based on the ER approach (Xu, McCarthy, and Yang, 2007), and the establishment a new ER rule considering weighted belief distribution with reliability (Yang and Xu, 2013), to name but a few.

The ER approach is characterised by a distributed modelling framework, an evidential reasoning algorithm, and the interval utility for ranking alternatives (Yang et al., 2006). Therefore, major advantages of applying the ER approach include (Yang and Xu, 2002; Yang et al., 2006; Riahi, 2010; Alyami et al., 2016; Wan et al., 2018):

- Being able to model both precise data and subjective judgments with uncertainties (e.g. incompleteness and vagueness) consistently under the unified framework.
- Being able to aggregate both complete and incomplete information.
- Being able to characterise incomplete assessments and rank alternatives.
- Provide users with the flexibility by allowing them to express their judgements both qualitatively and quantitatively.
- Provide a rational methodology for attribute aggregation based on its hierarchical evaluation process.

In this chapter, the ER approach is used for two purposes: firstly for aggregating the estimations of all the identified risk factors (which are obtained by using the BR-BN approach) in order to calculate the overall risk condition of every single MCSC, and then for evaluating the resilience impact of each MCSC on the maritime supply network with the help of sensitive analysis. The ER algorithm will be elaborated along with the research steps in the next section.

6.3 Methodology

The proposed framework for comprehensively evaluating MCSC performance consists of four major components, which outline all the necessary steps required for the estimation of risk factors at the bottom level of a hierarchical system and synthesis from the bottom level to the top level using the ER approach. These steps are described in a stepwise manner as follows:

Step 1. Develop a hierarchical structure for the performance evaluation of maritime supply networks.

Step 2. Assess the risk condition of MCSCs.

Step 3. Evaluate the impact of each MCSC on the resilience of the whole supply network by using sensitivity analysis.

Step 4. Validate the proposed approach.

6.3.1 Develop the Hierarchical Structure

Supposing there are *m* different MCSCs serving within the supply network and *n* risk factors being identified for the risk assessment of MCSCs, then the hierarchical structure can be developed according to the research purpose, as shown in Figure 6.1. The hierarchy for performance evaluation of MCSCs is mainly composed of three levels. The bottom level is constructed according to the risk classification framework of MCSCs proposed in Chapter 3. It consists of four sub-levels reflecting the relationships among different risk types, sources, and specific risk factors. The five major risk sources considered in this research are social risks, natural risks, operational risks, infrastructure and technology risks, and managerial risks. There are altogether 64 risk factors being selected, and all the risk factors investigated in this framework are identified through the combination of document review, field investigation, and Delphi expert surveys. The bottom level provides a basis for the risk assessment of MCSCs from a local perspective, while the top level reflects the performance of the maritime container supply network composed of the MCSCs under investigation. Thus, the top level offers a way to study the importance of each MCSC by quantifying its impact on the resilience of the supply network from a global perspective. The medium level shows the purpose of the study, aiming to comprehensively evaluate the performance of MCSCs and rank them taking into consideration both their local risk conditions and global impact on the supply network resilience.

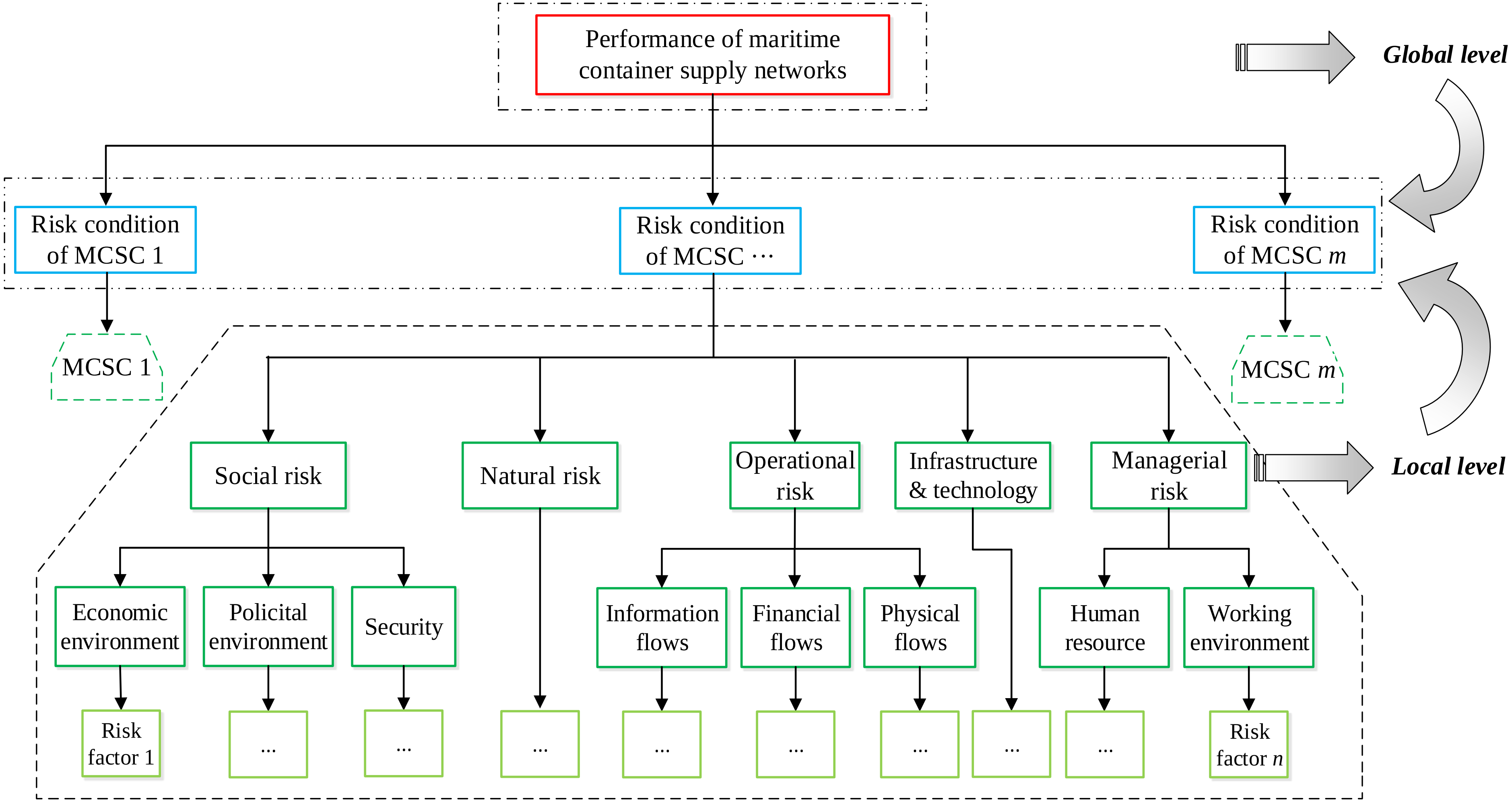


Figure 6.1. The hierarchy for the comprehensive evaluation of MCSC performance

6.3.2 Assess the Risk Condition of Each Single MCSC

The estimations of all the risk factors identified in the research can be presented in either linguistic variables with DoB or crisp values based on utility functions, as the risk assessment results in Chapter 4. The results expressed by linguistics variables will be used as the inputs in the ER approach for calculating the risk conditions of MCSCs. The usage of the ER algorithm in this research can be explained as follows (Yang and Xu, 2002).

Let two subsets R_1 and R_2 present the risk status of two risk factor 1 and 2 (in this research, there are three risk status expressions, i.e., *Low*, *Medium*, and *High*), and R be the synthesised risk status of the two risk factors. Then, R_1, R_2, and R can be expressed by:

$$R_1 = \{(Low, \beta_1^1), (Medium, \beta_1^2), (High, \beta_1^3)\} \qquad \text{Eq. 6.1}$$

$$R_2 = \{(Low, \beta_2^1), (Medium, \beta_2^2), (High, \beta_2^3)\} \qquad \text{Eq. 6.2}$$

$$R = \{(Low, \beta^1), (Medium, \beta^2), (High, \beta^3)\} \qquad \text{Eq. 6.3}$$

Where, *Low*, *Medium*, and *High* are associated with their corresponding DoBs. The estimations R_1 and R_2 are obtained by using the BR-BN approach proposed in Chapter 4 with the risk assessment information collected from the questionnaire survey.

Suppose the normalised relative weights of risk factors 1 and 2 in the risk assessment process are given as w_1 and w_2, where $w_1 + w_2 = 1$. w_1 and w_2 can be estimated according to the *ARI* values through the following equations.

$$w_1 = \frac{ARI_1}{\sum_{i=1}^{l} ARI_i} \qquad \text{Eq. 6.4}$$

$$w_2 = \frac{ARI_2}{\sum_{i=1}^{l} ARI_i} \qquad \text{Eq. 6.5}$$

where, l indicates the number of risk factors in the risk source under investigation. The *ARI* values of risk factors can be calculated using Eq. 3.5. (Refer to Chapter 3).

Suppose M_1^m and M_2^m (m = 1, 2, 3) are individual degrees to which the subsets R_1 and R_2 support the hypothesis that risk assessment is confirmed to the three risk status expressions. Then M_1^m and M_2^m can be calculated as follows (Alyami et al., 2016):

$$M_1^m = w_1 \beta_1^m \quad \text{Eq. 6.6}$$

$$M_2^m = w_2 \beta_2^m \quad \text{Eq. 6.7}$$

where, m = 1, 2, 3 in this research.

Suppose H_1 and H_2 are the individual remaining belief values unassigned for M_1^m and M_2^m (m = 1, 2, 3). Then, H_1 and H_2 are expressed as follows (Yang and Xu, 2002):

$$H_1 = \bar{H}_1 + \tilde{H}_1 \quad \text{Eq. 6.8}$$

$$H_2 = \bar{H}_2 + \tilde{H}_2 \quad \text{Eq. 6.8}$$

Where $\bar{H}_n (n = 1 \; or \; 2)$ represents the degree to which the other risk factors can play role in the assessment and $\tilde{H}_n (n = 1 \; or \; 2)$ is caused by the possible incompleteness in the subsets R_1 and R_2. They can be described as follows (Alyami et al., 2016):

$$\bar{H}_1 = 1 - w_1 \quad \text{Eq. 6.10}$$

$$\bar{H}_2 = 1 - w_2 \quad \text{Eq. 6.11}$$

$$\tilde{H}_1 = w_1 \left(1 - \sum_{m=1}^{3} \beta_1^m \right) \quad \text{Eq. 6.12}$$

$$\tilde{H}_2 = w_2 \left(1 - \sum_{m=1}^{3} \beta_2^m \right) \quad \text{Eq. 6.13}$$

Suppose that $\beta^{m'} (m = 1, 2, 3)$ represents the non-normalised degree to which the risk assessment is confirmed to each of the three risk status expressions as a result of the synthesis of the judgements produced by risk factor 1 and 2. Suppose H_U' represents the non-normalised remaining belief unassigned after the commitment of belief to the three risk status expressions resulting from the synthesis of the judgements produced by risk factor 1 and 2. The ER algorithm is stated as (Riahi et al., 2012):

$$\beta^{m'} = K(M_1^m M_2^m + M_1^m H_2 + M_2^m H_1) \quad \text{Eq. 6.14}$$

$$\bar{H}_U^{'} = K(\bar{H}_1 \bar{H}_2) \quad \text{Eq. 6.15}$$

$$\tilde{H}_U^{'} = K(\tilde{H}_1 \tilde{H}_2 + \tilde{H}_1 \bar{H}_2 + \tilde{H}_2 \bar{H}_1) \quad \text{Eq. 6.16}$$

Where K is a normalising factor that can be calculated as (Alyami et al., 2016):

$$K = \left(1 - \sum_{s=1}^{3} \sum_{\substack{t=1 \\ t \neq s}}^{3} M_1^s M_2^t \right)^{-1} \quad \text{Eq. 6.17}$$

After all assessments have been aggregated, the combined DoBs are generated by assigning $\bar{H}_U'$ back to the three risk expressions using the following normalisation process (Yang and Xu, 2002; Alyami et al., 2016):

$$\beta^m = \frac{\beta^{m'}}{1 - \bar{H}_U^{'}} \qquad \text{(m = 1, 2, 3)} \quad \text{Eq. 6.18}$$

$$H_U = \frac{\tilde{H}_U^{'}}{1 - \bar{H}_U^{'}} \quad \text{Eq. 6.19}$$

where H_U is the unassigned DoBs representing the extent of incompleteness in the overall assessment.

The above gives the process of combining two subsets representing the assessments of two risk factors. If three risk factors are required to be combined, the result obtained from the combination of any two sets can be further synthesised with the third one using the above algorithm. Similarly, multiple risk factors within the same risk source can be combined. In this way, the risk assessment results can be combined level by level from the bottom to the top of the hierarchy so as to investigate the risk condition of the whole MCSC.

6.3.3 Impact Analysis of MCSCs on the Resilience of the Whole Supply Network

The risk condition of MCSCs will be taken as the inputs in this step, which will be synthesised by using the ER algorithm again in order to evaluate the overall performance of the maritime supply network. According to the aggregating process introduced in Section 6.3.2, the weight of each MCSC within the supply network needs to be determined before synthesising them for the performance evaluation of the whole supply network. In this study, it is achieved by using the network-based indicators on the basis of the results from Chapter 5.

From a physical flow viewpoint, ports and shipping routes can be abstracted as nodes and links in a maritime transportation network. Under this vein, an MCSC can be regarded as a particular shipping route in the maritime transportation network, which is regularly used for container ships starting from the port of shipment, going through ports of call in a certain order, and ending at the port of destination (can be whether the same as the port of shipment or not, depending on the type of certain shipping route under investigation). It was revealed that the weight of a link is strongly correlated with its product degree (Tang and Zhou, 2011), and this assumption has been supported by empirical evidence of real weighted transportation networks such as air networks (Barrat et al., 2004). Without loss of generality, suppose that the maritime supply network is composed of x MCSCs and the MCSC under investigation is composed of y ports. Thus, the importance of each route section consisting of an MCSC can be assigned as (Holme et al., 2002):

$$L_{ab} = \left(S_O(a)S_O(b)\right)^{\theta} \qquad \text{Eq. 6.20}$$

Where θ is a tuneable weight parameter (which is usually set as 1), and $S_O(a)$ and $S_O(b)$ are the overall importance score of ports a and b ($a, b = 1, 2, \ldots, y$; $a \neq b$) with respect to their individual degree, closeness, and betweenness centralities in the maritime transportation network, which can be obtained using Eq. 5.11. Supposing that cargos are transported in a sequence from port a to b, the overall importance of the whole MCSC can be calculated as the sum of the importance of each section composing the MCSC, expressed as:

$$W_{\text{mcsc}} = \sum_{\substack{a=1 \\ b=a+1}}^{y-1} L_{ab} \qquad \text{Eq. 6.21}$$

Therefore the relative weight of each MCSC within the supply network can be calculated as:

$$w(c) = \frac{W_{\text{mcsc}}(c)}{\sum_{c=1}^{x} W_{\text{mcsc}}(c)} \qquad \text{Eq. 6.22}$$

It is noted that the synthesised results of the maritime supply network performance obtained from the aggregating process are generally presented in the form of linguistic terms with their associated DoBs. This will hinder the comparison and ranking of MCSCs in terms of their impacts on the resilience of the whole maritime transportation system because linguistic terms (e.g., good, average, poor) are not sufficient to show the difference between the results. Numerical values, therefore, need to be generated from the obtained distributed results. Following the ER algorithm, the concept of expected utility is introduced to obtain a crisp value of performance of maritime supply networks.

Suppose the utility of a performance evaluation grade of maritime supply network H_n is denoted by $u(H_n)$ and $u(H_{n+1}) > u(H_n)$ if H_{n+1} is preferable to H_n (Yang, 2001). $u(H_n)$ can be estimated by the decision maker's preference (Riahi et al., 2012). In this research, there are three evaluation grades associated with the performance of a maritime supply network, which are *Poor*, *Average*, and *Good*. The utility of each evaluation grade is respectively assigned as follows (Yang, Ng and Wang, 2014):

$$\begin{aligned} u\left(H_{Poor}\right) &= 1 \\ u\left(H_{Avg.}\right) &= 10 \\ u\left(H_{Good}\right) &= 100 \end{aligned} \qquad \text{Eq. 6.23}$$

The utility of the performance of maritime supply networks (top-level) E is denoted by $u(E)$. If $\beta_H \neq 0$ (which means that the assessment is incomplete, $\beta_H = 1 - \sum_{n=1}^{N} \beta_n$), there is a belief interval $[\beta_n, (\beta_n + \beta_H)]$, providing the likelihood that E is assessed to H_n. Without loss of generality, suppose that the least-preferred linguistic term having the lowest utility is denoted by $u(H_1)$ (e.g., $u(H_{Poor}) = 1$) and the most preferred linguistic term having the highest utility is denoted by $u(H_N)$ (e.g., $u(H_{Good}) = 100$). Then the minimum, maximum and average utilities of E are defined as (Riahi et al., 2012):

$$u_{\min}\left(E\right) = \sum_{n=2}^{N} \beta_n u(H_n) + (\beta_1 + \beta_H) u(H_1) \qquad \text{Eq. 6.24}$$

$$u_{\max}\left(E\right) = \sum_{n=1}^{N-1} \beta_n u(H_n) + (\beta_N + \beta_H) u(H_N) \qquad \text{Eq. 6.25}$$

$$u_{\text{average}}\left(E\right) = \frac{u_{\min}\left(E\right) + u_{\max}\left(E\right)}{2} \qquad \text{Eq. 6.26}$$

Obviously, if all the assessments are complete, then $\beta_H = 0$, and the maximum, minimum and average utilities of E will be the same. Therefore, $u(E)$ can be calculated as (Yang and Xu, 2002; Wan et al., 2017):

$$u\left(E\right) = \sum_{n=1}^{N} \beta_n u(H_n) \qquad \text{Eq. 6.27}$$

The above utilities are used only for characterising an assessment and not for criteria aggregation.

After the transformation of the linguistic evaluation results into numerical values, sensitivity analysis is required to evaluate MCSCs' resilience impact by measuring the influence magnitude of each MCSC on the performance of the entire supply network. The sensitivity analysis approach proposed in this chapter takes into account the specific risk condition of MCSCs (locally) obtained from the structured risk factors and their resilience impact on a container maritime supply network simultaneously. Firstly, the performance of the real maritime container supply network case is calculated based on the empirical data collected from questionnaire surveys. This value reflects the real performance of the targeted supply network in a normal situation (SP_N), which can be regarded as a baseline of the supply network performance. Secondly, the DoBs associated with the linguistic term *High* of an MCSC of the supply network are increased to 100% to check the performance of the supply network in the extreme case of risk (SP_E). In a similar way, the risk condition of each MCSC within the supply network can be reset to the extreme situation one by one. Lastly, the difference between SP_N and SP_E shows the resilience impact (RI) of each MCSC on the entire container shipping network and can be calculated as:

$$RI = SP_N - SP_E \qquad \text{Eq. 6.28}$$

The RI reflects the overall importance of an MCSC on a maritime logistics system level.

6.3.4 Validate the Proposed Method Using Sensitivity Analysis

Due to the lack of statistics data of container shipping opeartions and the novelty of this model, so far it is not possible to find any proven benchmark results for its full validation. Given the situation, a proper way to achieve the full validation of the model may be by using an incremental process, through conducting more industrial case studies so that the developed model can be refined and applied in real industrial applications. Based on the above, the model is partially validated using sensitivity analysis. Sensitivity analysis refers to analysing how sensitive the conclusions (i.e. model outputs) are to a minor change in the inputs. It is worth noting that the integrated approach proposed in this chapter is actually a two-layer model, and the validation of both layers of the model will be carried out together. If the integrated model is sound and the aggregation and inference processes are logical, then the sensitivity analysis must at least pursue the following two axioms (Alyami et al., 2016).

Axiom 1. A slight increment/decrement in the DoB associated with any assessment grades of a selected risk factor (lowest level) will certainly result in the effect of a relative increment/decrement in the risk condition of an MCSC and that of a relative decrement/increment in the performance of the entire supply network.

Axiom 2. The total influence magnitudes of the combination of the risk condition variations from x MCSCs (evidence) on the performance of the entire maritime network should always be greater than the one from the set of $x - y$ ($y \in x$) MCSCs (sub evidence).

It is noteworthy that it is possible to define other axioms for further research.

6.4 Case Study: From A Shipping Company's Perspective

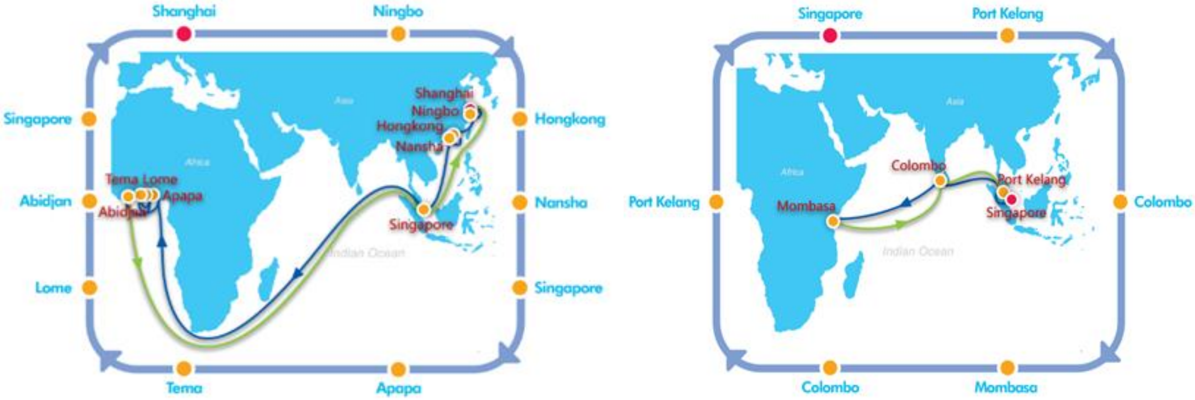
COSCO, a world-leading container shipping company in China, was selected to conduct a real case study to demonstrate the feasibility of the proposed method in the comprehensive evaluation of MCSC performance. It is considered to be a representative selection for the case study owing to the important role it plays in the container shipping industry. More detailed information about COSCO in terms of its global ranking, shipping capacity, and market share can be found in Section 5.4. The service on Asia/Africa Trade Lane offered by COSCO will be taken as an illustration. The case study will focus on risks associated with MCSC operations, as operational risk has been recognised as a crucial part in container logistics attracting attention from both industry and academia, e.g., Drewry (2009), Chang, Xu, and Song (2014), and Luo and Shin (2016).

6.4.1 Hierarchical Structure for Operational Performance of MCSCs in Africa

According to the schedule information of container shipping service, COSCO's Africa regional container supply network is composed of five major MCSCs, namely, FAX Service, ASA Service, AEF Service, ASEA Service, and FWAS Service. There are altogether 36 container ships serving 41 port pairs, which covers the eastern, western, and southern parts of Africa. The port rotation of these MCSCs is depicted in Figure 6.2.

FAX Service ASA Service

ASEA Service



FWAS Service AEF Service

Figure 6.2. Liner services associated with Africa region

Source: COSCO’s website (http://lines.coscoshipping.com/home/Services/route)

Based on the service information and the 26 identified operational risk factors, the hierarchical structure for the operational evaluation of MCSCs in Africa region can be constructed, as shown in Figure 6.3.

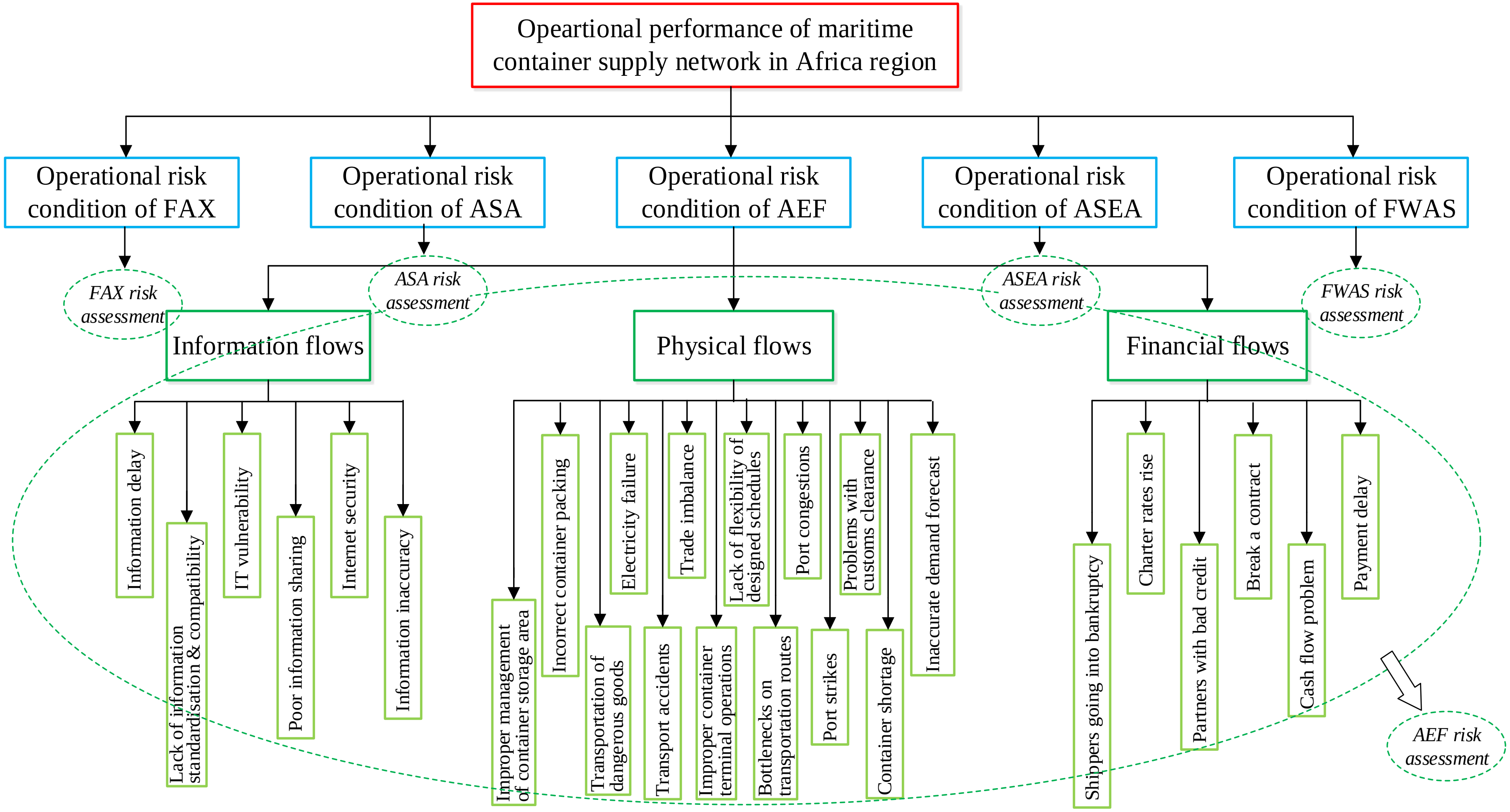


Figure 6.3. The hierarchical structure for the operational performance evaluation of MCSCs associated with Africa

6.4.2 Local Assessment of Risk Condition of MCSCs

A questionnaire was designed (see Appendix Eight) to collect risk assessment information on the 26 identified operational risk factors with respect to the MCSCs. For the risk assessment of each MCSC, seven respondents were selected who have been involved in the operational aspects related to the investigated MCSC, such as the shipping route design, ship scheduling, operations management, and voyaging on the investigated MCSCs. Thus, altogether 35 respondents participated in the questionnaire survey, and they all have rich working experience in the container shipping industry (at least ten years). Regarding the assessment of risk factors with respect to each MCSC, the feedback received from the seven experts is combined using a weighted average. Since the knowledge and experience of the experts selected for the case study are considered as equivalent, the normalised relative weight of every expert is equally assigned while merging their judgments on the risk factors. Taking the risk factor "information delay" as an illustration, if three experts agree that on the targeted MCSC, the occurrence likelihood of information delay is *Low*, and the feedback from the other four indicates an assessment of *Medium*, then, the DoB distribution of assessment on the information delay in terms of its likelihood can be expressed as {(*Low*, 42.9%), (*Medium*, 57.1%), (*High*, 0%)}, which can be simplified as (0.429, 0.571, 0). In a similar way, the judgements of every operational risk factor in terms of different risk parameters were collected and combined. Based on that, the risk status of each risk factor can be calculated by using Eq. 4.4, and the results with respect to different MCSCs are summarised in Table 6.1.

Table 6.1. Combined DoBs of risk factors with respect to different MCSCs

Operational risk factors	Associated with FAX	Associated with ASA	Associated with AEF	Associated with AESA	Associated with FEAS
Op/IF_1	(0.71, 0.25, 0.04)	(0.65, 0.31, 0.04)	(0.68, 0.29, 0.03)	(0.69, 0.28, 0.03)	(0.73, 0.23, 0.04)
Op/IF_2	(0.66, 0.32, 0.02)	(0.7, 0.28, 0.02)	(0.6, 0.35, 0.05)	(0.64, 0.33, 0.03)	(0.68, 0.27, 0.05)
Op/IF_3	(0.58, 0.35, 0.07)	(0.57, 0.36, 0.07)	(0.59, 0.3, 0.11)	(0.52, 0.36, 0.12)	(0.59, 0.16, 0.25)
Op/IF_4	(0.59, 0.34, 0.07)	(0.52, 0.41, 0.07)	(0.48, 0.34, 0.18)	(0.49, 0.34, 0.17)	(0.54, 0.24, 0.22)
Op/IF_5	(0.56, 0.24, 0.2)	(0.46, 0.28, 0.26)	(0.47, 0.27, 0.26)	(0.37, 0.37, 0.26)	(0.41, 0.34, 0.25)
Op/IF_6	(0.65, 0.27, 0.08)	(0.72, 0.18, 0.1)	(0.78, 0.12, 0.1)	(0.74, 0.16, 0.1)	(0.75, 0.13, 0.12)
Op/FF_1	(0.86, 0.14, 0)	(0.85, 0.15, 0)	(0.72, 0.28, 0)	(0.78, 0.22, 0)	(0.81, 0.19, 0)
Op/FF_2	(0.79, 0.21, 0)	(0.73, 0.27, 0)	(0.62, 0.38, 0)	(0.59, 0.41, 0)	(0.52, 0.48, 0)
Op/FF_3	(0.63, 0.25, 0.12)	(0.55, 0.22, 0.23)	(0.49, 0.3, 0.21)	(0.49, 0.26, 0.25)	(0.54, 0.22, 0.24)
Op/FF_4	(0.54, 0.41, 0.05)	(0.55, 0.41, 0.04)	(0.58, 0.38, 0.04)	(0.51, 0.49, 0)	(0.6, 0.37, 0.03)
Op/FF_5	(0.56, 0.33, 0.11)	(0.56, 0.3, 0.14)	(0.66, 0.19, 0.15)	(0.64, 0.21, 0.15)	(0.59, 0.27, 0.14)
Op/FF_6	(0.4, 0.42, 0.18)	(0.34, 0.48, 0.18)	(0.23, 0.48, 0.29)	(0.23, 0.49, 0.28)	(0.34, 0.45, 0.21)
Op/PF_1	(0.6, 0.27, 0.13)	(0.61, 0.27, 0.12)	(0.58, 0.27, 0.15)	(0.51, 0.3, 0.19)	(0.58, 0.14, 0.28)
Op/PF_2	(0.17, 0.34, 0.49)	(0.17, 0.32, 0.51)	(0.1, 0.26, 0.64)	(0, 0.25, 0.75)	(0.05, 0.24, 0.71)
Op/PF_3	(0.38, 0.42, 0.2)	(0.4, 0.42, 0.18)	(0.36, 0.44, 0.2)	(0.3, 0.47, 0.23)	(0.4, 0.34, 0.26)

Op/PF_4	(0.23, 0.4, 0.37)	(0.3, 0.26, 0.44)	(0.22, 0.26, 0.52)	(0.18, 0.25, 0.57)	(0.25, 0.27, 0.48)
Op/PF_5	(0.35, 0.37, 0.28)	(0.34, 0.39, 0.27)	(0.38, 0.31, 0.31)	(0.41, 0.26, 0.33)	(0.31, 0.22, 0.47)
Op/PF_6	(0.51, 0.47, 0.02)	(0.51, 0.48, 0.01)	(0.46, 0.52, 0.02)	(0.41, 0.58, 0.01)	(0.49, 0.49, 0.02)
Op/PF_7	(0.55, 0.3, 0.15)	(0.51, 0.35, 0.14)	(0.4, 0.28, 0.32)	(0.33, 0.37, 0.3)	(0.55, 0.2, 0.25)
Op/PF_8	(0.27, 0.45, 0.28)	(0.34, 0.36, 0.3)	(0.14, 0.59, 0.27)	(0.12, 0.61, 0.27)	(0.3, 0.38, 0.32)
Op/PF_9	(0.51, 0.39, 0.1)	(0.44, 0.45, 0.11)	(0.42, 0.43, 0.15)	(0.39, 0.46, 0.15)	(0.31, 0.42, 0.27)
Op/PF_10	(0.27, 0.58, 0.15)	(0.24, 0.59, 0.17)	(0.14, 0.61, 0.25)	(0.14, 0.61, 0.25)	(0.27, 0.46, 0.27)
Op/PF_11	(0.49, 0.48, 0.03)	(0.43, 0.54, 0.03)	(0.5, 0.47, 0.03)	(0.54, 0.43, 0.03)	(0.53, 0.44, 0.03)
Op/PF_12	(0.37, 0.31, 0.32)	(0.31, 0.34, 0.35)	(0.39, 0.29, 0.32)	(0.36, 0.31, 0.33)	(0.25, 0.44, 0.31)
Op/PF_13	(0.7, 0.24, 0.06)	(0.71, 0.21, 0.08)	(0.63, 0.31, 0.06)	(0.71, 0.22, 0.07)	(0.71, 0.14, 0.15)
Op/PF_14	(0.58, 0.41, 0.01)	(0.45, 0.54, 0.01)	(0.42, 0.58, 0)	(0.46, 0.54, 0)	(0.44, 0.54, 0.02)

According to the *ARI* values presented in Table 3.16, the weight of each risk factor at the same level can be calculated by using Eq. 6.4. Taking the risk factors associated with the information flow as an illustration:

$$w_{\text{Op/IF\_1}} = \frac{ARI_{\text{Op/IF\_1}}}{\sum ARI_{\text{Op/IF}}} = \frac{6.38}{6.38+6.64+6.11+6.08+5.8+5.77} = 0.173$$

Similarly, the weights of every operational risk factors can be obtained and summarised in Table 6.2.

Table 6.2. The weight of risk factors at different levels

Item	Weight	Item	Local weight
Information flow	0.325	Op/IF_1	0.173
		Op/IF_2	0.181
		Op/IF_3	0.166
		Op/IF_4	0.165
		Op/IF_5	0.158
		Op/IF_6	0.157
Financial flow	0.340	Op/FF_1	0.171
		Op/FF_2	0.170
		Op/FF_3	0.163
		Op/FF_4	0.160
		Op/FF_5	0.166
		Op/FF_6	0.170
Physical flow	0.335	Op/PF_1	0.075
		Op/PF_2	0.082
		Op/PF_3	0.068
		Op/PF_4	0.067
		Op/PF_5	0.079
		Op/PF_6	0.067
		Op/PF_7	0.067
		Op/PF_8	0.068
		Op/PF_9	0.068

		Op/PF_10	0.071
		Op/PF_11	0.069
		Op/PF_12	0.072
		Op/PF_13	0.078
		Op/PF_14	0.069

Once the estimations and relative weights of individual risk factors have been obtained, the risk condition of MCSC operations can be assessed by synthesising the estimations of all risk factors in the hierarchical structure using the ER algorithm (i.e. Eqs. 6.6 to 6.19). A detailed synthesis process of risk factors “information delay” and “information inaccuracy” with respect to FAX can be found in Appendix Nine. It is noted that the results can also be achieved by using the IDS software package which was developed by Yang and Xu (2013) to realise the fast calculation. Accordingly, the estimations of risk factors at the bottom level can be combined and then the aggregating process is conducted upwards from the bottom level. Then, the risk condition of each MCSC can be obtained. An example of the evaluation results of FAX by using the IDS software package is shown in Figure 6.4.

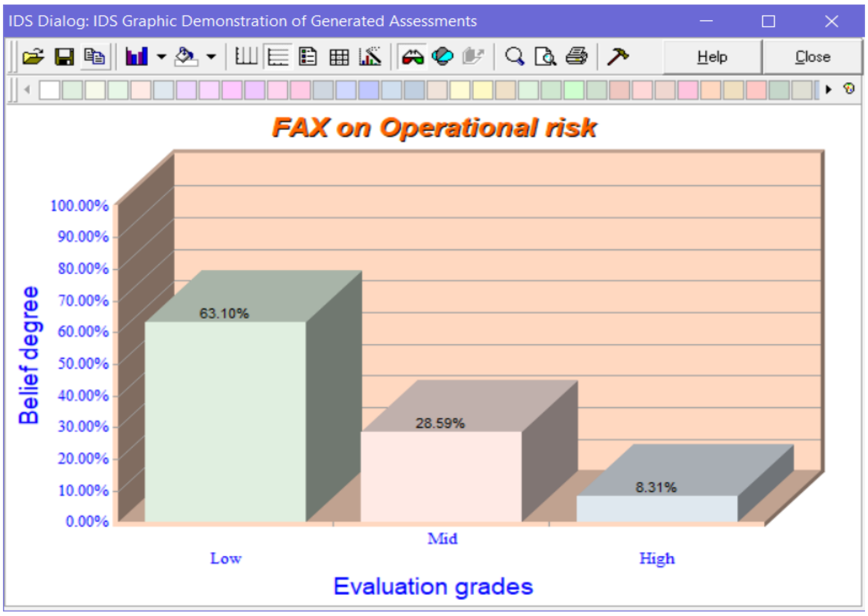


Figure 6.4. A screenshot of the evaluation result of FAX

By using the utility functions as described by Eq. 6.23, where $u(H_{Low}) = 1$, $u(H_{Medium}) = 10$, and $u(H_{High}) = 100$, the excepted risk values of each MCSC can be calculated. The risk conditions of shipping routes and their risk values are summarised in Table 6.3.

Table 6.3. Operational risk condition of MCSCs

MCSCs	Risk condition associated with operations	Utility values
FAX	{(*Low*, 63.1%), (*Medium*, 28.6%), (*High*, 8.3%)}	11.791
ASA	{(*Low*, 60.2%), (*Medium*, 30.2%), (*High*, 9.6%)}	13.222
AEF	{(*Low*, 56.1%), (*Medium*, 31.7%), (*High*, 12.2%)}	15.931
ASEA	{(*Low*, 53.6%), (*Medium*, 33.6%), (*High*, 12.8%)}	16.696
FWAS	{(*Low*, 59.0%), (*Medium*, 26.7%), (*High*, 14.3%)}	17.560

It is noteworthy to mention that, in terms of the utility values of the risk condition of MCSCs, the higher the value, the higher the risk level of the MCSC.

6.4.3 Resilience Analysis of MCSCs' performance

In this step, the weight of each MCSC will be calculated, and the risk condition of MCSCs will then be aggregated in order to evaluate the overall performance of the supply network. According to the shipping route information of each MCSC and the overall scores of every port (refer to Appendix Seven for more information) being involved in the targeted MCSC, the weights of MCSCs can be obtained by using Eqs. 6.20, 6.21, and 6.22, as summarised in Table 6.4.

Correlation analysis shows that the correlation coefficient between the importance of an MCSC and the container shipping capacity deployed on the MCSC is 0.88. The close relationship indicates that the proposed model for calculating MCSCs' structural importance reflects the reality to a large extent. Once the relative weight of each MCSC is obtained, the performance of the entire supply network can be evaluated by applying the ER algorithm again, through which the risk conditions of MCSCs are aggregated.

Table 6.4. Relative weight and shipping capacity of MCSCs in Africa

No.	MCSCs	Relative weight	Shipping capacity
1	FAX	0.147	6 × 4200 TEU
2	ASA	0.288	7 × 4200 TEU
3	AEF	0.134	5 × 2800 TEU
4	ASEA	0.130	6 × 2600 TEU
5	FWAS	0.301	12 × 3500 TEU

Next step is to quantify the resilience impact of each MCSC on the container shipping supply network in Africa and identify the most significant one using the sensitivity analysis approach. In order to test the resilience impact of each MCSC, five different extreme scenes are set in the sensitivity analysis, where the DoB belonging to the linguistic variable *High* is increased to

100% in turn with respect to each MCSC. The variations of performance between the normal situation and those extreme ones are calculated using Eqs. 6.23 and 6.27. For example, as the performance of the supply network under normal situation is estimated to be {(*Poor*, 10.1%), (*Average*, 27.2%), (*Good*, 62.7%)}, its expected value can be calculated as:

$$u\left(SP_N\right)=\sum_{n=1}^{3}\beta_n u(H_n)=0.101\times1+0.272\times10+0.627\times100=65.521$$

It is worth noting that three linguistic variables used to assess the risk condition of MCSCs are *Low*, *Medium*, and *High* (which are as same as the ones used for risk factors assessment), while the performance of the supply network (in the top level of the hierarchy) is expressed by linguistic variables *Poor*, *Average*, and *Good*. Thus, a mapping process is required to transform the different types of linguistic terms in different levels into the same plate (Yang, Ng and Wang, 2014). Observe that there is a negative correlation between the two sets of variables, which means that the lower the risk condition/level an MCSC is, the better the performance the network will be. Both the levels apply three assessment grades, and the relationship between them is elucidated in Figure 6.5.

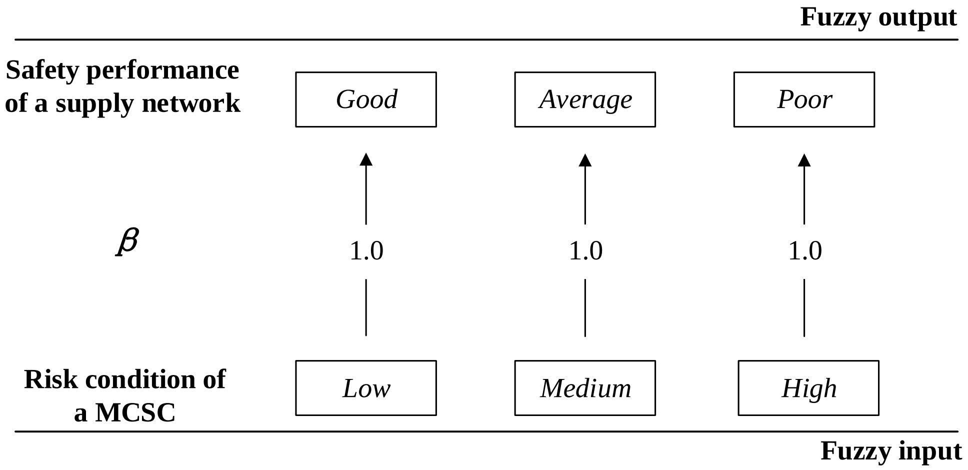


Figure 6.5. Mapping from risk condition to operational performance

Explanations of different scenes along with the excepted utilities under various risk scenarios are summarised in Table 6.5. It can be seen that the broken of different shipping routes leads to different degrees of deterioration of the supply network performance, among which the shutdown of FWAS route influences the most. However, it is also worth noting that the whole network can still remain the operational function to a large extent even under the most severe risk scenario, showing its resilience in the face of external disturbance.

Table 6.5. Performance of the supply network under different scenarios

Normal situation		SP_N	Extreme scenario 1		$SP_{E\text{-}FAX}$
FAX	(0.631, 0.286, 0.083)	65.521	FAX	(0, 0, 1)	53.497
ASA	(0.602, 0.302, 0.096)		ASA	(0.602, 0.302, 0.096)	
AEF	(0.561, 0.317, 0.122)		AEF	(0.561, 0.317, 0.122)	
ASEA	(0.536, 0.336, 0.128)		ASEA	(0.536, 0.336, 0.128)	
FWAS	(0.590, 0.267, 0.143)		FWAS	(0.590, 0.267, 0.143)	
Extreme scenario 2		$SP_{E\text{-}ASA}$	Extreme scenario 3		$SP_{E\text{-}AEF}$
FAX	(0.631, 0.286, 0.083)	52.228	FAX	(0.631, 0.286, 0.083)	56.683
ASA	(0, 0, 1)		ASA	(0.602, 0.302, 0.096)	
AEF	(0.561, 0.317, 0.122)		AEF	(0, 0, 1)	
ASEA	(0.536, 0.336, 0.128)		ASEA	(0.536, 0.336, 0.128)	
FWAS	(0.590, 0.267, 0.143)		FWAS	(0.590, 0.267, 0.143)	
Extreme scenario 4		$SP_{E\text{-}ASEA}$	Extreme scenario 5		$SP_{E\text{-}FWAS}$
FAX	(0.631, 0.286, 0.083)	57.160	FAX	(0.631, 0.286, 0.083)	41.824
ASA	(0.602, 0.302, 0.096)		ASA	(0.602, 0.302, 0.096)	
AEF	(0.561, 0.317, 0.122)		AEF	(0.561, 0.317, 0.122)	
ASEA	(0, 0, 1)		ASEA	(0.536, 0.336, 0.128)	
FWAS	(0.590, 0.267, 0.143)		FWAS	(0, 0, 1)	

According to Eq. 6.28, the *RI* values of each MCSC within the supply network can be obtained, as shown in the following.

$$RI_{FAX} = SP_N - SP_{E\text{-}FAX} = 65.521 - 53.497 = 12.024$$

$$RI_{ASA} = SP_N - SP_{E\text{-}ASA} = 65.521 - 52.228 = 13.293$$

$$RI_{AEF} = SP_N - SP_{E\text{-}AEF} = 65.521 - 56.683 = 8.838$$

$$RI_{ASEA} = SP_N - SP_{E\text{-}ASEA} = 65.521 - 57.16 = 8.361$$

$$RI_{FWAS} = SP_N - SP_{E\text{-}FWAS} = 65.521 - 41.824 = 23.697$$

Therefore, MCSCs can be prioritised in terms of their importance from different perspectives, as shown in Table 6.6.

Table 6.6. Ranking of MCSCs according to different types of priorities

MCSC	Local risk condition	Rank	Topological structure	Rank	*RI* Value	Rank
FAX	11.791	1	0.147	3	12.024	3
ASA	13.222	2	0.288	2	13.293	2
AEF	15.931	3	0.134	4	8.838	4
ASEA	16.696	4	0.130	5	8.361	5
FWAS	17.560	5	0.301	1	23.697	1

It can be seen that the FAX was the supply chain that has the best operational condition due to the relatively developed port infrastructure in Southern Africa. In contrast, FWAS was identified as the one with the highest operational risk level, which is closely related to its poor ground access systems to ports, relatively severely unbalanced trade volumes between import and export, and the increasing piracy in the Gulf of Guinea in recent years. However, FWAS was identified as the most important one in terms of its topological structure within COSCO's global container shipping network. This also results in its important position in terms of the operational resilience impact on the Africa supply network. Based on the above results, the shipping routes (i.e. FAX, ASA, AEF, ASEA, and FWAS) consisting of the MCSCs in the Africa region are removed one by one to test their cumulative impact on the performance of the whole network. The results are depicted in Figure 6.6.

It can be seen that when all shipping routes within the supply network are out of service, the operational performance of the container supply network gradually declines from the original status (65.521) to a total breakdown (0) (rather than a sharp drop), showing its good resilience when experiencing disruptive events.

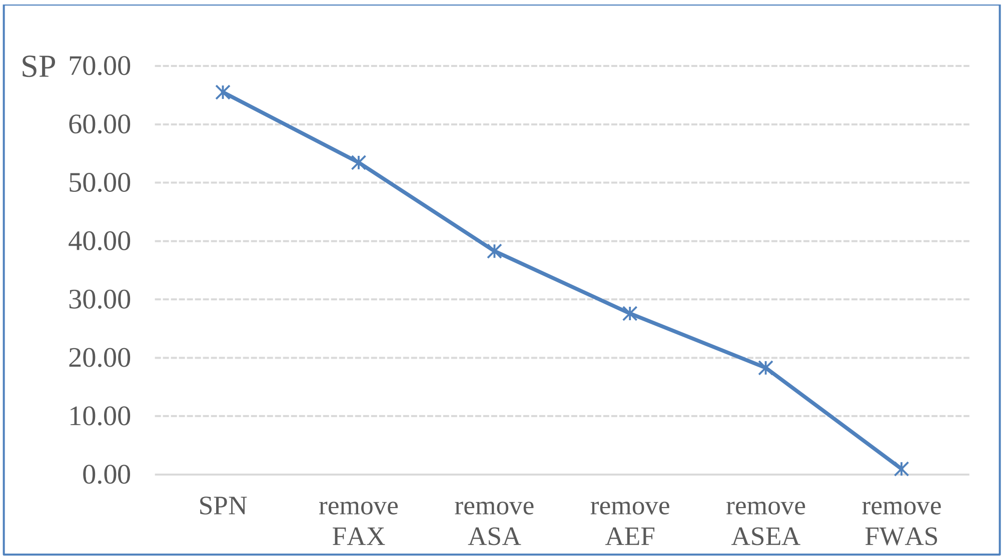


Figure 6.6. A drop of the operational performance after the shutdown of shipping routes

6.4.4 Validation of the Model

Two axioms introduced in Section 6.3.4 are used to validate the rationality of the proposed model and test the logicality of the delivery of the analysis results. As the sensitivity of the BR-BN approach has already been tested in Chapter 4, this chapter will mainly focus on the novel part of the proposed model, i.e., the aggregation process using the ER approach.

The risk factor “information delay” (Op/IF_1) and the FAX supply chain is selected for the tests. The DoB associated with the linguistic term *High* is increased by 0.1 and, simultaneously, the DoB associated with the linguistic term *Low* is decreased by 0.1. Its impact is that the risk condition of FAX increased from 0.2261 to 0.2650, and the performance of the Africa container supply network decreased accordingly. Similar studies were conducted on 26 operational risk factors, and all the results obtained remain in harmony with Axiom 1. This reveals that the risk condition of MCSCs and performance of the entire transportation network are sensitive to the identified risk factors.

Table 6.7. Influence magnitude of risk factors on the risk condition of FAX

No.	**Risk factors**			**Risk condition**	**Variation of value**
	Op/IF_1	Op/FF_1	Op/PF_1		
1	-	-	-	11.791	-
2	0.1			12.205	0.414
3		0.1		12.295	0.504
4			0.1	11.998	0.207
5	0.1	0.1		12.808	1.017
6	0.1		0.1	12.502	0.711
7		0.1	0.1	12.601	0.810
8	0.1	0.1	0.1	13.015	1.224

0.1 means a 10% reassignment of DoB in risk factors moving toward the maximal increment of risk level.

The same DoB change (i.e. 0.1 increment in *High* and 0.1 decrement in *Low*) is applied to the other risk factors such as “payment delay from partners” (Op/FF_1), and “inaccurate demand forecast” (Op/PF_1) (one random risk factor from each of the information, financial and physical flow is selected respectively), and the combined impact of such changes on the risk condition of MCSCs and the performance of the entire supply network is checked. The obtained results are shown in Table 6.7 and 6.8, respectively.

Table 6.8. Influence magnitude of MCSCs on the resilience of the supply network

No.	**MCSCs**					**Performance**	**Variation of value**
	FAX	ASA	AEF	ASEA	FWAS		
1	-	-	-	-	-	65.521	-
2	0.1					63.757	1.764
3		0.1				63.469	2.052
4			0.1			64.054	1.467
5				0.1		64.054	1.467
6					0.1	61.894	3.627
7	0.1	0.1				61.606	3.915
8	0.1		0.1			62.191	3.330
9	0.1			0.1		62.191	3.330

10	0.1				0.1	59.932	5.589
11		0.1	0.1			61.903	3.618
12		0.1		0.1		61.903	3.618
13		0.1			0.1	59.734	5.787
14			0.1	0.1		62.488	3.033
15			0.1		0.1	60.229	5.292
16				0.1	0.1	60.328	5.193
17	0.1	0.1	0.1			60.040	5.481
18	0.1	0.1		0.1		60.040	5.481
19	0.1	0.1			0.1	57.772	7.749
20	0.1		0.1	0.1		60.625	4.896
21	0.1		0.1		0.1	58.366	7.155
22	0.1			0.1	0.1	58.366	7.155
23		0.1	0.1	0.1		60.328	5.193
24		0.1	0.1		0.1	58.069	7.452
25		0.1		0.1	0.1	58.169	7.352
26			0.1	0.1	0.1	58.753	6.768
27	0.1	0.1	0.1	0.1		58.465	7.056
28	0.1	0.1	0.1		0.1	56.197	9.324
29	0.1	0.1		0.1	0.1	56.197	9.324
30	0.1		0.1	0.1	0.1	56.791	8.730
31		0.1	0.1	0.1	0.1	56.494	9.027
32	0.1	0.1	0.1	0.1	0.1	54.532	10.989

0.1 means a 10% reassignment of DoB in each MCSC moving toward the maximal decrement of the performance of the supply network.

According to Axiom 2, if the model reflects the logical reasoning, then the influence magnitude for risk condition of FAX associated with the combination *x* of risk factors (evidence) should always be greater than the one from *x*-*y* ($y \in x$) (sub-evidence). The No. 2 risk condition (in Table 6.7) is chosen as the sub-evidence to investigate the accuracy of the model. Other combinations of risk factors that are affected by the variation given to the DoB associated with linguistic variable *High* including No.5 and No.8 can be identified as the evidence. By comparing the evidence and sub-evidence, it can be seen that risk condition value in the second row (0.414) is always smaller than that in the fifth (1.017) and eighth (1.224) row. A similar phenomenon can also be observed in terms of the influence magnitude of MCSCs on the performance of the entire supply network, as presented in Table 6.8. Taking combination No. 17 as an example (evidence), its impact on the performance of the sample supply network can be calculated as 5.481 (=65.521-60.040). Then, the impact of its sub-evidence on the supply network performance can be calculated and shown as No.2, 3, 4, 7, 8, and 11. Comparing all the relevant impacts of such evidence and sub-evidence, 5.481 is the one with the most influence. Therefore, the model is validated in the selected example. The additional investigation was conducted using other combinations of risk factors and MCSCs. The results are consistent with Axiom 2, supporting the soundness and logic of the model.

6.5 Conclusions

In this chapter, a novel approach is proposed incorporating different advanced risk modelling and assessment techniques in a complementary way so as to achieve the comprehensive evaluation of MCSC performance from a systematic perspective. An empirical case study is conducted from a shipping company's perspective, and the results confirm that the proposed method is capable of presenting sensitive and flexible risk results in real situations and providing a powerful tool for container shipping risk management. Although the case study of the proposed model in this chapter mainly focused on the operational aspects including information, financial, and physical flows, leaving the other risk sources from the risk classification framework such as managerial, natural environment, and political issues (see Chapter 3) to be addressed in future work, the proposed method still highlights its potential in facilitating overall risk assessment of operations in a wide context when being appropriately tailored to study other maritime supply chains, such as the global cargo supply chain and the global tanker supply chain, with more information and data being collected from a wider range and higher level. The risk-based resilience impact analysis is also believed to be significant for establishing suitable risk control options and selecting optimum ones to eliminate or mitigate the risk factors in the global container logistics system and to enhance its robustness and efficiency. Last but not least, the combination of the Hugin and IDS software is also helpful in facilitating real-time decision making under dynamic conditions.

It is also noteworthy that the proposed framework provides a standard, generic method for the evaluation of MCSC performance. Although it is applied and demonstrated in a case study of the container shipping industry, it has the potential and flexibility to be tailored to meet the needs of the application in different supply chain industries. However, the specific risk factors under investigation may vary, and the developed BRB for risk reference (of the selected risk factors) needs to be reconstructed. In the new rule base, inputs from multiple domain experts need to be appropriately verified to ensure practical and non-biased belief functions (Yang et al., 2008) fitting the newly investigated supply chain context. Further, different risk parameters, as well as variables used to estimate the risk parameters, may be selected according to the feature of other industries and specific requirements of risk assessment.

CHAPTER 7 - CONCLUSIONS AND FUTURE RESEARCH

Summary

This chapter summarises the research findings on the identification, classification, and assessment of risk factors associated with the container shipping industry in all previous chapters. It also highlights the advantages of the proposed models and techniques in the safety design, operation and management of MCSCs. Several limitations of the research are outlined, along with the opportunities arising from the developed methods for future improvement and applications.

7.1 Conclusions and Contribution of the Research

Containerisation is an essential and crucial part of the rapid development of global trade and international transportation. However, the increasing complexities and globalisation pose significant challenges for the safety and efficiency of maritime transportation operations. As a focal part connecting global supply chains, MCSCs involve multiple stakeholders from different segments such as sea, rail and road transport. Thus, the proper risk management of MCSCs is of great significance, and the need to appropriately estimate and control the risks involved in MCSCs by advanced approaches is appreciated by both academics and industrial participants in order to ensure personnel safety, enhance operational efficiency, and improve the reliability of the whole system.

The findings from the literature review have revealed that previous studies have only focused on one or several particular types of risk of MCSCs, and rarely did they inclusively examine all of the possible risk factors and evaluate the relative importance of each of them. Besides, most of the studies paid more attention to the analysis of the local risk of certain segments within an MCSC, having their relationships with other parts of the chain neglected, let alone the overall influence of MCSCs on the performance of the entire container maritime transportation network. These MCSCs with higher weights, traffic volumes, and shipping connections, are believed to be more important compared to the others in terms of ensuring supply network resilience. Thus, the previous chapters of this thesis have developed an integrated framework for the comprehensive evaluation of MCSC performance based on a range of advanced risk assessment and network analysis approaches. The framework has been constructed in a generic sense which is able to deal with both engineering and managerial problems. The applied methods and research outcomes can be concluded as follows:

1) Providing a novel risk classification framework and identifying a comprehensive list of risk factors within the container shipping industry (Chapter 3).
2) Categorising the identified risk factors into different risk levels by using the risk matrix approach with primary data collected from the different stakeholders involved in an MCSC (Chapter 3).
3) Applying BN to model FRB for the assessment of risk factors of MCSCs. More risk parameters are considered to extend the traditional risk concept in supply chain risk management (Chapter 4)
4) Proposing a new indicator for measuring the overall importance of ports in maritime transportation networks by incorporating degree, closeness and betweenness centrality together (Chapter 5).
5) Using the ER approach to synthesise the estimations of risk factors to achieve the risk assessment of MCSCs (Chapter 6).
6) Applying the ER approach and the sensitivity analysis to evaluate the resilience impact of MCSCs on the entire container maritime supply network (Chapter 6).

Although the approaches and methods proposed in this thesis are developed based on certain application situations, it is believed that these methods possess great potential as valuable and powerful tools to assist the stakeholders in the risk management and decision making of MCSCs and will gain more usage in the MCSC emergency planning and response. Moreover, these methods can be tailored according to the specific applications in practice to deal with operational problems in other transportation systems with different purposes and requirements, especially in situations where there is a high level of uncertainty. The implementation of the proposed methods could benefit real-life applications. A more specific description of the research contributions in terms of academic and practical aspects are provided as follows:

- In the maritime shipping industry, risks usually appear in a variety of forms which will impact on diverse parts of an MCSC. It is therefore essential to comprehensively identify risk factors existing in MCSCs. The novel multi-dimensional, multi-level and multi-actor framework proposed for identifying and classifying risk factors in MCSCs, together with the comprehensive analysis based on the empirical data, provide a panorama picture of risk factors in MCSCs. The novelty of the classification framework can be seen via some emerging risk factors that are identified in *Chapter 3* such as refugee immigrants, ergonomics-related risks, and improper management of container storage areas. This can be a reflection of increasing complexity in the global supply chain environment. The research results empirically contribute to the literature and knowledge of supply chain risk management as few studies so far have investigated the risks in MCSCs from a systematic perspective using empirical data. Based on the empirical data collected through a large scale survey of industry experts, a bridge between the theoretical and applied research of MCSCs can be built in a timely manner, which helps to realise the difference of understanding of risks in the maritime container shipping between academics and practitioners.

- Regarding the classification and screening of the identified risk factors, the comprehensive analysis of the risk factors from multiple dimensional aspects in MCSCs is of great importance in the shipping industry. For example, the information on the quantitative importance analysis (i.e. *ARI*) of each risk factor will be helpful for the stakeholders to understand which parts deserve more attention in the whole maritime supply chain so as to rationalize their safety resource allocation for accident prevention. Moreover, by incorporating the well-established ALARP principle into the risk matrix approach, the risk factors can be appropriately categorised into four different risk levels, which can help maritime safety authorities to effectively develop targeted risk mitigation countermeasures under different risk situations within the context of MCSCs.

- In the risk assessment research, it is noteworthy that *Chapter 4* introduces a novel quantitative method for risk assessment of MCSC risks by incorporating fuzzy logic and brief rule-based method into BNs. This combination provides a powerful tool to incorporate subjective judgments to evaluate risks and prioritise risk factors under uncertainty, as system risk analysis often requires using domain experts' knowledge when risk records are incomplete. Further, representing risk inputs as a probability distribution on linguistic variables enables different types of uncertain information to be modelled using a unified form. The BR-BN method holds great potential in risk-based designing and planning due to its ability to instantly rank the risk factors of a container supply chain according to the stakeholders' needs with updated information, by which the real-time requirement in the industry can also be satisfied.

- Although the FRB method has been well established in the risk assessment context, its applications in risk management of maritime container transportation, especially with the consideration of more supply chain-targeted risk attributes, are relatively new. Based on traditional definitions of the risk concept, more attributes are explored within the context of MCSCs in order to better and more accurately measure the associated risk factors. Classifying risk consequences into different categories can also generate useful information for managers with respect to different decision-making requirements. Besides, using the same/equivalent sets of linguistic grades for both IF and THEN segments simplifies the communication between risk inputs and outputs based on DoBs. This facilitates practical implementation in the maritime industry. Meanwhile, considering the weight of each antecedent attribute creates more robust DoBs compared to the existing studies in the literature.

- A new indicator for measuring the importance of ports in the global maritime transportation network is developed in *Chapter 5*. The multi-centrality indicator aggregates the information from different centrality measures (e.g. degree, closeness, and between-ness centrality) by using the Borda Count method so that it can provide the whole profile of ports when ranking them according to their positions in the container shipping network and provide a more comprehensive evaluation result for aiding rational decisions. The consideration of container throughput of ports provides a rational way to determine the weight of each individual centrality measure when aggregating them for the overall importance score. The method is capable of providing insights on the identification of vulnerability in MCSCs, which contributes to generating valuable managerial implications for the stakeholders such as container lines and port authorities to ensure the robustness of the MCSCs.

- Assessment of a single risk factor cannot reflect the overall risk condition of an MCSC, which inevitably hinders the proper and efficient risk management of supply chains. The ER algorithm is applied to aggregate the estimations of each risk factor from different risk sources together in order to provide an overview of the risk condition of the whole MCSC. Moreover, the importance of each MCSC within the container maritime transportation network is taken into consideration so as to investigate the resilience impact of individual MCSCs on the performance of the entire supply network. This facilitates a more systematic analysis from an overall perspective being able to consider the combined influences of both the local risk condition of an MCSC and its global impact on the whole logistics system. To the best of author's knowledge, this kind of work has not yet been seen in the previous research of supply chain risk management.

7.2 Limitations of Research and Future Research

The research has achieved its aim of providing an integrated framework for risk modelling and assessment of MCSCs in a complex and uncertain environment. However, due to the time and cost constraints, some problems in the current study have not been fully explored, which may be necessary and desirable in future investigation. The limitations of this research are identified as:

1) Regarding the risk classification framework proposed in Chapter 3, it is inevitable that there may be a certain extent of correlation existing among the identified risk factors under different risk types. However, the level of correlation among these risk factors is not clear which calls for more hard empirical evidence. Thus, in the current study, it is assumed that all the identified risk factors are independent, which may not fully in line with the real-life situation. Besides, it would be better if the screening results of risk factors can be further validated with careful experts judgments due to the inherent mathematical limitations of the traditional risk matrices.
2) The questionnaire survey is used to classify the identified risk factors and address the risk assessment with five risk parameters due to incomplete data, but it is acknowledged that both the size of the sampling population and the subjective nature of the responses could be a source of bias. Besides, due to the cost consideration and the time limit, only 132 valid questionnaire replies were obtained in the survey. Thus, it would be better if more empirical data could be collected to validate the results further.
3) This thesis uses a Chinese shipping company as a representative in the case study of constructing the sample container shipping network and performance measurement of MCSCs. It is believed that the results would be more accurate if the author had incorporated service information from other international container shipping companies worldwide. Also, it would be useful if a comparative study could be conducted to involve more inputs from other actors in the same supply chain such as freight

forwarders, logistics service providers, and port operators and investigate the features of other maritime transportation networks in terms of different types of cargo.

4) This thesis mainly focuses on the identification and assessment of risk factors of MCSCs, with no more analysis related to the decision making which is also important in terms of a complete process of risk management. It would be useful if relevant decision-making tools can be developed based on the evaluation results of the current study.
5) Complex risk inference and calculation processes are involved in the integrated framework for the comprehensive evaluation of MCSC performance, which is not friendly to unsophisticated users in practice. It would be useful if more convenient computing software can be developed to facilitate the industrial implications of the proposed models and approaches.

Aiming to deal with the above-mentioned limitations, the current research can be extended in the following aspects:

- Due to the lack of accurate industry-specific data, questionnaire surveys are applied for generating risk input based on the five risk parameters in the methodology. In the current study, the target respondents are mainly selected from academia and industry in the UK and China. In order to improve the findings for their better generalisation, future work is needed to collect more responses from international MCSC companies, located in different countries and regions. Besides, incorporation of objective risk data in terms of both likelihood and consequence derived from accident investigation reports and accident databases may also be needed to verify the findings further.

- Another issue that has not been well addressed is the non-homogenous nature of the participants involved in the questionnaire survey, which means that the factors such as their work experience, age, and position may have some impact on their perception of risks. In the future, this issue can be further investigated by, for example, introducing the dominant factor which will be used to adjust the impact level of each expert's/ participant's judgments in the aggregation stage of the methodology.

- The container maritime transportation network constructed in *Chapter 5* can be further extended in the future work by taking into consideration the service information of other world-leading liner shipping companies including APM-Maersk, Mediterranean

Shipping Co, CMA CGM Group, and Hapag-Lloyd, to name but a few. This will contribute to a more accurate global container shipping network model in terms of the reflection of its topological structure and connections among ports. A comparative study of different container shipping companies is also expected to shed some light on the issue of the measurement of port position and MCSC importance in a maritime supply network.

- As identified by the risk factor classification framework, many types of risks exist in MCSCs. This study investigated the risk assessment of operational aspects of MCSCs as an illustrative case of the proposed integrated approach. It would be interesting to consider multiple types of risks by incorporating risk inputs from other risk sources (i.e. social risk, natural environment risk, managerial risk, and infrastructure and technology risk) so that more complete results can be obtained.

- Last but not least, future work may be needed to propose risk control options and resilience strategies, as well as to develop effective decision-making tools in order to reduce/eliminate the factors with high risk levels and enhance the container supply chain's efficiency and resilience. Besides, more resilience characteristics identified in Chapter 2 may be incorporated to improve the current evaluation framework and offer more insight into the risk management of MCSCs for both academia and industry.

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Appendices

Appendix One

Delphi expert survey on the classification and identification of risk factors

Section A: Structure of the framework for risk factor classification

Our research focuses on the containers maritime transportation, which is mainly composed of two parts, i.e. port operations and seaborne transportation. Thus, risk factors generated from relevant processes are identified, while those particularly associated with land transportation (e.g. road and rail) are not considered in this study. Risk factors of Maritime Container Supply Chains (MCSCs) in this study refer to the occurrence of triggering events, or certain situations, which would result in adverse such as human injury, property and/or environmental damage, business interruption, and reputation loss, influencing any component of an MCSC.

Question 1. The framework presented in Figure 1 is developed based on academic literature, textbooks, and information from the internet. Could you please modify it if there is anything wrong or inappropriate in terms of the structure and components of this framework?

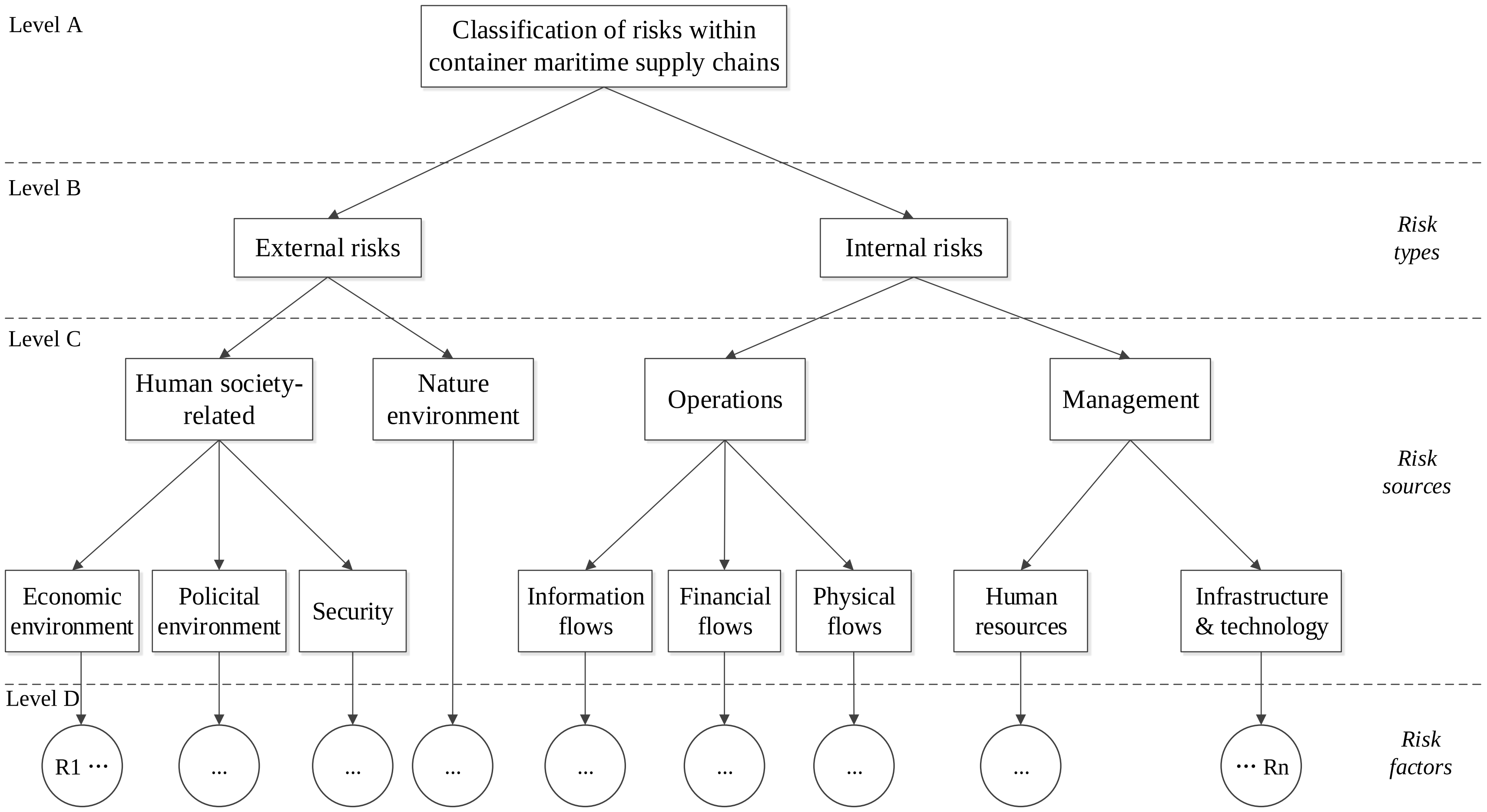

Figure 1 Structure of the framework for risk factor classification

Section B: Identification of risk factors

Question 1. What are the possible risk factors in an MCSC based on your knowledge and experience?

Question 2. The following tables are the risk factors associated with different parts of an MCSC system that I summarised from existing studies. Do you think they exist in the container shipping industry? How about your company?

Question 3. Do you think there are any other risk factors that are not mentioned in the list? Please add them to the related tables.

Table 1. Risk factors of *economic environment*

Risk source	**Risk factors**
Economic environment	R1. Financial crisis
	R2. Change of interest rates
	R3. Change of exchange rates
	R4. Fluctuation of fuel price
	R5. Unattractive markets
	R6. Fierce competition
	R7. Monopoly [9]
	Please add that any other risk factors should be considered

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[9] For example, forwarding agency, shipping company, or terminal's monopoly

Table 2. Risk factors of *political environment*

Risk source	**Risk factors**
Political environment	R1. Political instability
	R2. Maritime security initiatives [10]
	R3. Different customs' policies
	R4. Government regulations
	Please add that any other risk factors should be considered

Table 3. Risk factors of *security*

Risk source	**Risk factors**
Security	R1. Terrorism
	R2. Regional conflict
	R3. Pirate /maritime robbery
	R4. Sabotage
	R5. Smuggling
	R6. Spying /espionage
	R7. Epidemic
	Please add that any other risk factors should be considered

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[10] E.g. container security initiative (CSI), 24-h rule, Megaports Initiative, etc.

Table 4. Risk factors of *nature environment*

Risk source	**Risk factors**
Nature environment	R1. Changeable weather conditions
	R2. Nature hazards
	R3. Climate change
	Please add that any other risk factors should be considered

Table 5. Risk factors of *information flows*

Risk source	**Risk factors**
Information flows	R1. Information delay
	R2. Information inaccuracy
	R3. IT vulnerability [11]
	R4. Interpretation problems with documents, contracts and permits
	R5. Internet security [12]
	R6. Poor information sharing
	R7. Lack of information standardisation and compatibility
	R8. Intellectual property
	Please add that any other risk factors should be considered

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[11] E.g. IT infrastructure breakdown or crash

[12] Such as risk of intrusion or fraud

Table 6. Risk factors of *financial flows*

Risk source	**Risk factors**
Financial flows	R1. Payment delay from partners
	R2. Break a contract
	R3. Bankruptcy of shippers
	R4. Partners with bad credit
	Please add that any other risk factors should be considered

Table 7. Risk factors of *physical flows*

Risk source	**Risk factors**
Physical flows	R1. Demand fluctuation
	R2. Transportation of dangerous goods
	R3. Container shortage
	R4. Port strikes
	R5. Port/ terminal congestions
	R6. Lack of flexibility of designed schedules [13]
	R7. Problems with customs clearance
	R8. Electricity failure [14]
	R9. Bottlenecks/ restriction in the transportation routes
	R10. Improper container terminal operations
	R11. Incorrect container packing
	R12. Transport accidents [15]
	Please add that any other risk factors should be considered

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[13] Such as no alternative transport solution.
[14] Which may happen during reefer container shipping, or port operations.
[15] Such as ship contract, grounding, sinking, collision on quay, and oil spill.

Table 8. Risk factors of *human resources*

Risk source	**Risk factors**
Human resources	R1. Lack of skilled workers
	R2. Lack of motivation
	R3. Mental health problems [16]
	R4. Language and cultural diversity
	R5. Lack of cooperation among departments
	R6. Poor safety culture/climate
	R7. Low degree of safety leadership [17]
	Please add that any other risk factors should be considered

Table 9. Risk factors of *Infrastructure and technology*

Risk source	**Risk factors**
Infrastructure & technology	R1. Lack of intermodal equipment
	R2. Poor channel condition
	R3. Limited storage ability
	R4. Low technical reliability
	R5. The undeveloped ground access system of a port
	Please add that any other risk factors should be considered

---

[16] Such as fatigue, stress and anxiety of workers

[17] Lack of safety motivation, safety policy, and safety concern.

Appendix Two

Revision report of the classification framework and risk factors

Based on the valuable comments from the Delphi expert group, the original framework for risk factor classification has been revised. Some indicators are added (or modified) while some others are deleted either due to the high correlations with other risk factors or because of the little consistency with the actual situation in the container shipping industry. The revised framework based on experts with rich industrial experience will be more pragmatic in terms of conducting empirical studies.

In the rest of this report, the revised framework is shown in Figure 1, and the modified and newly added risk factors are highlighted in Table 1 to 5, respectively. Finally, the specific reasons for all of the modifications are also reported, presented in Table 6.

For Delphi expert survey

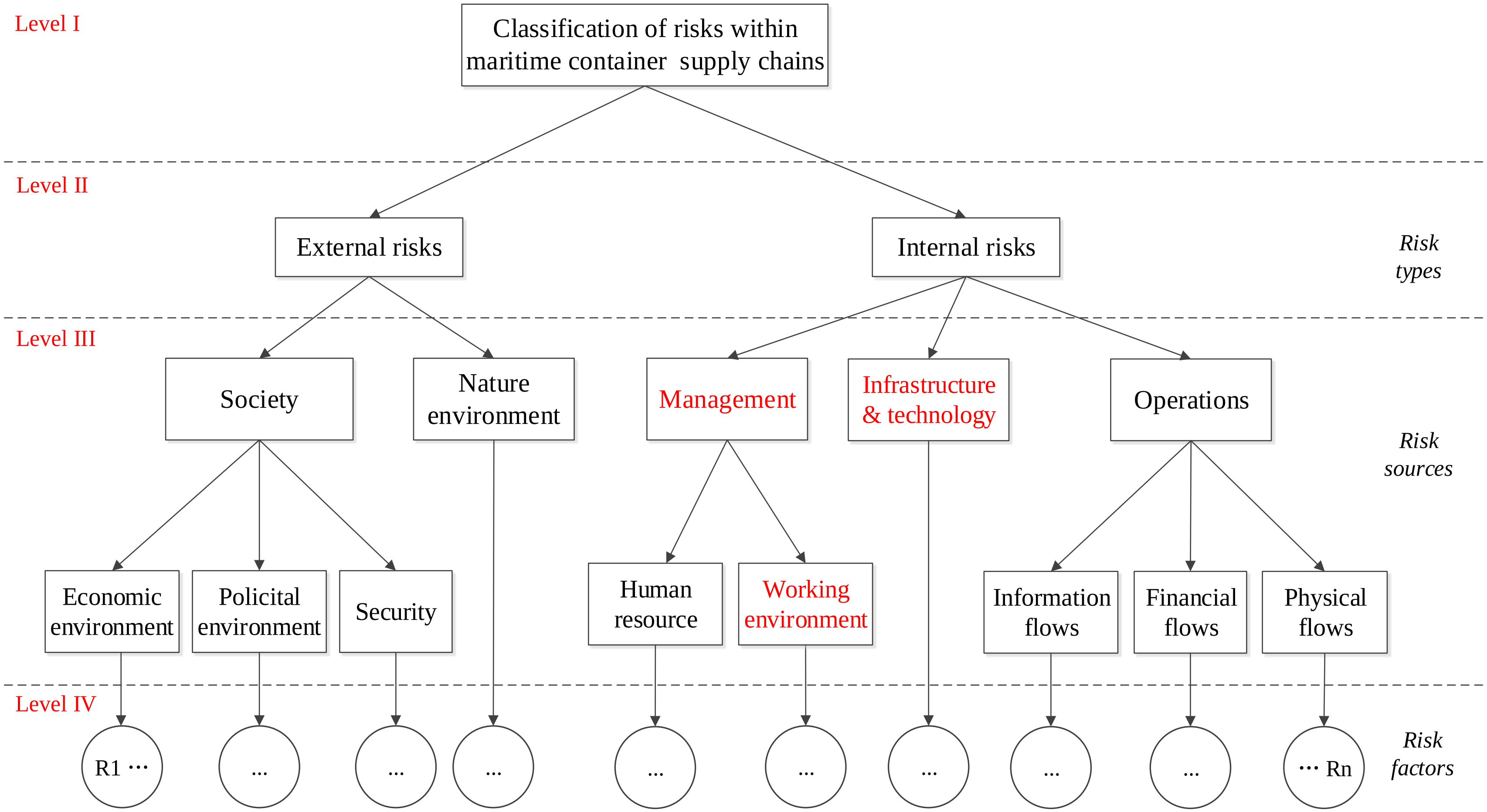

Figure 1. Structure of the framework for risk factor classification

For Delphi expert survey

Table 1. Risk factors associated with *Society*

Risk factors of *economic environment* (EE)	
R1. Financial crisis	HS/EE_1
R2. Change of interest rates	HS/EE_2
R3. Change of exchange rates	HS/EE_3
R4. Fluctuation of fuel price	HS/EE_4
R5. Unattractive markets	HS/EE_5
R6. Fierce competition	HS/EE_6
R7. Monopoly [18]	HS/EE_7
Risk factors of *political environment* (PE)	
R1. Trade policy instability [19]	HS/PE_1
R2. Maritime security initiatives [20]	HS/PE_2
R3. Regulations and measures [21]	HS/PE_3
R4. Regional political conflicts	HS/PE_4
Risk factors of *security* (SE)	
R1. Terrorism	HS/SE_1
R2. Piracy /maritime robbery	HS/SE_2
R3. Sabotage	HS/SE_3
R4. Smuggling	HS/SE_4
R5. Spying /espionage	HS/SE_5
R6. Epidemic	HS/SE_6
R7. Refugee immigrants	HS/SE_7

Table 2. Risk factors associated with *Nature Environment*

R1. Changeable weather conditions	NE_1
R2. Natural hazards [22]	NE_2
R3. Climate change	NE_3

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[18] For example, forwarding agency, shipping company, or terminal's monopoly
[19] E.g. Brexit, fall of EU.
[20] E.g. container security initiative (CSI), 24-h rule, Megaports Initiative, etc.
[21] E.g. IMO's regulations, CO_2 reduction measures
[22] Such as tsunami, typhoon, flood, etc.

For Delphi expert survey

Table 3. Risk factors associated with *Management*

Risk factors of *human resource* (HR)	
R1. Lack of skilled workers	Man/HR _1
R2. Lack of motivation	Man/HR _2
R3. Mental health problems[23] of seafarers	Man/HR _3
R4. Human errors	Man/HR _4
R5. Unreasonable salary and welfare	Man/HR _5
Risk factors of *working environment* (WE)	
R1. Language and cultural diversity	Man/WE_1
R2. Lack of cooperation among departments	Man/WE_2
R3. Poor safety culture/climate	Man/WE_3
R4. Low degree of safety leadership [24]	Man/WE_4
R5. Poor ergonomics at the workplace	Man/WE_5

Table 4. Risk factors associated with *Infrastructure and Technology*

Risk factors of *infrastructure and technology* (I & T)	
R1. Lack of intermodal equipment	I & T _1
R2. Poor entrance channels of a port	I & T _2
R3. Limited storage ability	I & T _3
R4. Low technical reliability	I & T _4
R5. The undeveloped ground access system of a port	I & T _5
R6. Lack of regular maintenance of equipment	I & T _6
R7. Insufficient berthing capability	I & T _7

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[23] Such as fatigue, stress and anxiety of workers

[24] Lack of safety motivation, safety policy, and safety concern.

For Delphi expert survey

Table 5. Risk factors associated with *Operations*

Risk factors of *information flows* (IF)	
R1. Information delay	Op/IF_1
R2. Information inaccuracy	Op/IF_2
R3. IT vulnerability [25]	Op/IF_3
R4. Internet security [26]	Op/IF_4
R5. Poor information sharing	Op/IF_5
R6. Lack of information standardisation and compatibility	Op/IF_6
Risk factors of *financial flow* (FF)	
R1. Payment delay from partners	Op/FF_1
R2. Break a contract	Op/FF_2
R3. Shippers going into bankruptcy	Op/FF_3
R4. Partners with bad credit	Op/FF_4
R5. Charter rates rise	Op/FF_5
R6. Cash flow problem	Op/FF_6
Risk factors of *physical flow* (PF)	
R1. Inaccurate demand forecast	Op/PF_1
R2. Transportation of dangerous goods	Op/PF_2
R3. Container shortage	Op/PF_3
R4. Port strikes	Op/PF_4
R5. Port/ terminal congestions	Op/PF_5
R6. Lack of flexibility of designed schedules [27]	Op/PF_6
R7. Problems with customs clearance	Op/PF_7
R8. Electricity failure [28]	Op/PF_8
R9. Bottlenecks/ restriction in the transportation routes	Op/PF_9
R10. Improper container terminal operations[29]	Op/PF_10
R11. Incorrect container packing	Op/PF_11
R12. Transport accidents [30]	Op/PF_12
R13. Trade imbalance on container shipping routes	Op/PF_13
R14. Improper management of container storage area	Op/PF_14

For Delphi expert survey

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[25] E.g. IT infrastructure breakdown or crash

[26] Such as risk of intrusion or fraud

[27] Such as no alternative transport solution.

[28] Which may happen during reefer container shipping, or port operations.

[29] Such as loading, uploading, handling, etc.

[30] Such as ship contract, grounding, sinking, collision on quay, and oil spill.

Table 6. Reasons for the modifications of the classification framework and risk factors

Original structure of the framework		**Revised category**	**Reason**
Management	Modified	Working environment	It involves both physical conditions such as locations and surroundings and working atmosphere and culture of an organisation.
Internal risks	Modified	Infrastructure and technology	This is a fundamental element supporting functions of an MCSC. Thus, it should be on the same level as the category *management* and *operations*.
Level A to D	Modified	Level I to IV	It is more common to use Roman numerals (such as I, II, and III) rather than English letters when representing different hierarchical levels.
Original risk factors		**Revised risk factor**	**Reason**
Political Environment			
R1	Modified	HS/PE_1	The original risk factor emphasises on a national level, while the revised one (such as Brexit) is more accurate and direct considering its influence on international business activities.
R3	Replaced	HS/PE_3	The benefits of different customs policies far outweigh the disadvantages they may bring. Thus, the original risk factor is replaced by “regulations and measures” which impact the cost-effectiveness ratio of container shipping.
R4	Replaced	HS/PE_4	The new one is more specific.
Security			
R2	Deleted	/	It is abstractive and has an overlap with HS/PE_4.
/	Added	HS/SE_7	The refugee issue becomes a popular issue in recent years, especially in European countries. It may increase the probability of smuggling.
Human Resource			
R3	Modified	Man/HR _3	Seafarers are more likely to suffer from mental health problems due to the special working environment onboard.
/	Added	Man/HR _4	Most of the accidents are the results of human errors, which is inevitable to some extent. This further highlight the importance of this factor in daily management.
/	Added	Man/HR _5	This risk factor influences the labour cost of a company and the employees’ salary satisfaction.
Working Environment			
/	Added	Man/WE_5	This factor is important to the realisation of occupational health and safety and productivity.
Infrastructure and Technology			

For Delphi expert survey

R2	Modified	I & T _2	The original risk factor is vague, and thus it is revised using a more specific one instead.
/	Added	I & T _6	Regular maintenance of equipment can improve its technical status, and extend its life cycle, which will contribute to the safe operations and cost reduction.
/	Added	I & T _7	This may limit the throughput of a port, and result in the increase of waiting time for container ships.
Information Flow			
R4	Deleted	/	The format of cargo carriage contracts is relatively fixed.
R8	Deleted	/	Seldom does intellectual property will be a problem for the maritime container shipping.
Financial Flow			
R3	Modified	Op/FF_3	The original risk factor is revised using more accurate description.
/	Added	Op/FF_5	It is quite a common issue influence the cost of container shipping that should be considered.
/	Added	Op/FF_6	It can be vital to the survival and development of a company, especially for small businesses.
Physical Flow			
R1	Modified	Op/PF_1	The original one is regarded as a kind of external factors. It is one of the reasons which may result in inaccurate demand forecast from the perspective of operations.
/	Added	Op/PF_13	This risk factor is related to the proper operations of empty containers.
/	Added	Op/PF_14	This may reduce the effectiveness of port operations and cause accidents.

For Delphi expert survey

Appendix Three

Questionnaire on the measurement of risk factors in maritime container supply chains

Dear Sir/Madam,

My name is Chengpeng Wan; I am currently pursuing a PhD degree at the Liverpool Logistics Offshore and Marine Research Institute (LOOM) in Liverpool John Moores University. My research topic in the first technical chapter is “Identification of risk factors in maritime container supply chains”, which intends to identify and assess risk factors of container supply chains, with focus on the maritime logistics process. The purpose of the questionnaire is to measure the identified risk factors in maritime container supply chains, so as to select the significant ones.

I am writing to elicit your opinion as an executive in the whole process of the container maritime logistics with expert knowledge on risk assessment. Your participation is voluntary; however, your assistance would be greatly appreciated in making this a meaningful questionnaire. The information gathered in this survey will be treated in the strictest confidence, as this has always been the policy of the Liverpool John Moores University. This survey will take you about 10-15 minutes. This questionnaire is anonymous. Thus your response cannot be attributed to you or your company.

If you have any questions about this research, please contact me at +44-(0)777 087 3050, or by email at cpwan@whut.edu.cn, or my supervisor, Prof. Zaili Yang, by email z.yang@ljmu.ac.uk.

Please accept my thanks for your anticipated co-operation. If you wish to receive a copy of the research results, please email me at cpwan@whut.edu.cn (regardless of whether you participate or not).

Yours faithfully,

Chengpeng Wan,
PhD Candidate

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Section A: Respondent's Profile

We would like to ask you about how your research or business involves transportation operations in container maritime supply chains.

1. What is the type of your organisation?

☐ Academia ☐ Industry ☐ Governmental body ☐ Other

2. Which part of the process of a maritime container supply chain are you involved in?

☐ Port operations ☐ Maritime transportation ☐ the whole process

3. What is your research area or professional role?

____

4. What is your job title/position?

____

5. For how many years have you worked in the container shipping or related industry?

☐ 1-5 years ☐ 6-10 years ☐ 11-15 years ☐ 16-20 years ☐ >20 years

6. How many employees are in your company/organisation?

☐ 1-50 people ☐ 51-100 people ☐ 101-200 people ☐ 201-500 people ☐ >500 people

For the screening of the 64 identified risk factors, a 7×4 Risk Matrix is applied to determine their relative importance considering two dimensions, the likelihood and severity. In this research, the Likelihood Index (LI) is scored using 1, 2, 3, 4, 5, 6, and 7, shown in Table 1.

Table 1. Definitions of LI

Likelihood	**Likert scale**	**Definition**
Extremely Rare	1	Has never or rarely happened
Rare	2	Not expected to occur for a few years; May only occur in exceptional circumstances
Unlikely	3	Trivial likelihood, however, could occur at some time
Possible	4	Might occur at some time; Expected to occur every few months
Likely	5	Will probably occur in most circumstances; Expected to occur at least monthly
Frequent	6	Expected to occur at least weekly
Very Frequent	7	Can be expected to occur in most circumstances; Occur at least daily

While, the Severity Index (SI) of a risk factor is assigned a number from 1 to 4, shown in Table 2.

Table 2. Definitions of SI

Consequence severity	**Likert scale**	**Definition**
Minor	1	Cause some inconvenience with minor impacts such as small cost/schedule increase.
Moderate	2	Cause some disruptions with medium impacts such as moderate cost increase, delay, and minor environmental damage.
Severe	3	Cause some disruptions, or sometimes failures with severe impacts such as major cost increase, major environmental damage or injuries
Catastrophic	4	Cause complete and irrecoverable failures (thus the minimum requirements cannot be achieved), long-term environmental damage, or death

All identified risk factors are evaluated according to your experience and knowledge in view of the LI and SI. Related questions are presented in the following sections.

Section B: The following questions are related to risk factors associated with **society** in MCSCs. Please fill the appropriate score in each of the following boxes:

Risk factors of *economic environment* (EE)		**LI** (from 1 to 7)	**SI** (from 1 to 4)
R1. Financial crisis	HS/EE_1		
R2. Change of interest rates	HS/EE_2		
R3. Change of exchange rates	HS/EE_3		
R4. Fluctuation of fuel price	HS/EE_4		
R5. Unattractive markets	HS/EE_5		
R6. Fierce competition	HS/EE_6		
R7. Monopoly	HS/EE_7		
Risk factors of *political environment* (PE)			
R1. Trade policy instability	HS/PE_1		
R2. Maritime security initiatives	HS/PE_2		
R3. Regulations and measures	HS/PE_3		
R4. Regional political conflicts	HS/PE_4		
Risk factors of *security* (SE)			
R1. Terrorism	HS/SE_1		
R2. Piracy /maritime robbery	HS/SE_2		
R3. Sabotage	HS/SE_3		
R4. Smuggling	HS/SE_4		
R5. Spying /espionage	HS/SE_5		
R6. Epidemic	HS/SE_6		
R7. Refugee immigrants	HS/SE_7		

Section C: The following questions are related to risk factors associated with the **natural environment** in MCSCs. Please fill the appropriate score in each of the following boxes:

Risk factors of *natural environment* (NE)		**LI** (from 1 to 7)	**SI** (from 1 to 4)
R1. Changeable weather conditions	NE_1		
R2. Natural hazards	NE_2		
R3. Climate change	NE_3		

Section D: The following questions are related to risk factors associated with **management** in MCSCs. Please fill the appropriate score in each of the following boxes:

Risk factors of *human resource* (HR)		**LI** (from 1 to 7)	**SI** (from 1 to 4)
R1. Lack of skilled workers	Man/HR _1		
R2. Lack of motivation	Man/HR _2		
R3. Mental health of seafarers	Man/HR _3		
R4. Human errors	Man/HR _4		
R5. Unreasonable salary and welfare	Man/HR _5		
Risk factors of *working environment* (WE)			
R1. Language and cultural diversity	Man/WE_1		
R2. Lack of cooperation among departments	Man/WE_2		
R3. Poor safety culture/climate	Man/WE_3		
R4. Low degree of safety leadership	Man/WE_4		
R5. Poor ergonomics at workplace	Man/WE_5		

Section E: The following questions are related to risk factors associated with **infrastructure and technology** in MCSCs. Please fill the appropriate score in each of the following boxes:

Risk factors of *infrastructure and technology* (I & T)		**LI** (from 1 to 7)	**SI** (from 1 to 4)
R1. Lack of intermodal equipment	I & T _1		
R2. Poor entrance channels of a port	I & T _2		
R3. Limited storage ability	I & T _3		
R4. Low technical reliability	I & T _4		
R5. The undeveloped ground access system	I & T _5		
R6. Lack of regular maintenance of equipment	I & T _6		
R7. Insufficient berthing capability	I & T _7		

Section F: The following questions are related to risk factors associated with **operations** in MCSCs. Please fill the appropriate score in each of the following boxes:

Risk factors of *information flows* (IF)		**LI** (from 1 to 7)	**SI** (from 1 to 4)
R1. Information delay	Op/IF_1		
R2. Information inaccuracy	Op/IF_2		
R3. IT vulnerability	Op/IF_3		
R4. Internet security	Op/IF_4		
R5. Poor information sharing	Op/IF_5		
R6. Lack of information standardisation and compatibility	Op/IF_6		
Risk factors of *financial flow* (FF)			
R1. Payment delay from partners	Op/FF_1		
R2. Break a contract	Op/FF_2		
R3. Shippers going into bankruptcy	Op/FF_3		
R4. Partners with bad credit	Op/FF_4		
R5. Charter rates rise	Op/FF_5		
R6. Cash flow problem	Op/FF_6		
Risk factors of *physical flow* (PF)			
R1. Inaccurate demand forecast	Op/PF_1		
R2. Transportation of dangerous goods	Op/PF_2		
R3. Container shortage	Op/PF_3		
R4. Port strikes	Op/PF_4		
R5. Port/ terminal congestions	Op/PF_5		
R6. Lack of flexibility of designed schedules	Op/PF_6		
R7. Problems with customs clearance	Op/PF_7		
R8. Electricity failure	Op/PF_8		
R9. Bottlenecks/restriction on transportation routes	Op/PF_9		
R10. Improper container terminal operations	Op/PF_10		
R11. Incorrect container packing	Op/PF_11		
R12. Transport accidents	Op/PF_12		
R13. Trade imbalance on container shipping routes	Op/PF_13		
R14. Improper management of container storage area	Op/PF_14		

Appendix Four

Measurement of the weight of risk parameters

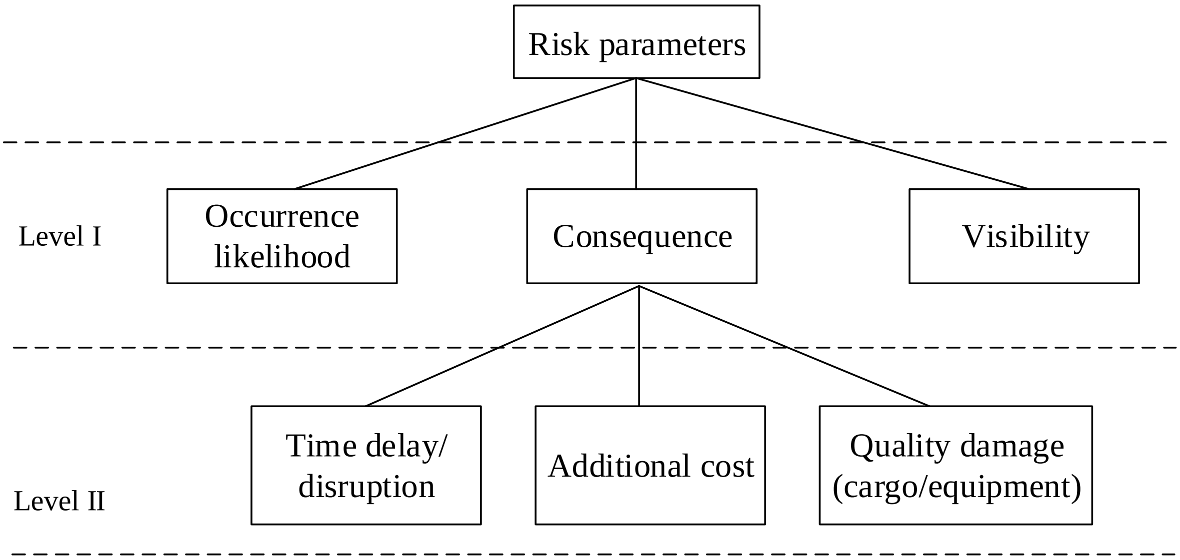

Figure 1 Parameters of MCSC risk

Table 1. Importance of risk parameters in Level I

<table>
<tr><th colspan="19">In Level I, which parameter do you think is more important? (please mark in the table)</th></tr>
<tr><td colspan="9">Increasing importance ←</td><td colspan="10">→ Increasing importance</td></tr>
<tr><td rowspan="2">Parameters</td><td><i>Extreme importance</i></td><td></td><td><i>Very strong</i></td><td></td><td><i>Strong importance</i></td><td></td><td><i>Moderate importance</i></td><td></td><td><i>Equal importance</i></td><td></td><td><i>Moderate importance</i></td><td></td><td><i>Strong importance</i></td><td></td><td><i>Very strong</i></td><td></td><td><i>Extreme importance</i></td><td rowspan="2">Parameters</td></tr>
<tr><td>9:1</td><td>8:1</td><td>7:1</td><td>6:1</td><td>5:1</td><td>4:1</td><td>3:1</td><td>2:1</td><td>1:1</td><td>1:2</td><td>1:3</td><td>1:4</td><td>1:5</td><td>1:6</td><td>1:7</td><td>1:8</td><td>1:9</td></tr>
<tr><td>Likelihood</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>Consequence</td></tr>
<tr><td>Likelihood</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>Visibility</td></tr>
<tr><td>Consequence</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>Visibility</td></tr>
</table>

Table 2. Importance of risk parameters in Level II

<table>
<tr><th colspan="19">In Level II, which parameter do you think is more important? (please mark in the table)</th></tr>
<tr><td colspan="9">Increasing importance ←</td><td colspan="10">→ Increasing importance</td></tr>
<tr><td rowspan="2">Parameters</td><td><i>Extreme importance</i></td><td></td><td><i>Very strong</i></td><td></td><td><i>Strong importance</i></td><td></td><td><i>Moderate importance</i></td><td></td><td><i>Equal importance</i></td><td></td><td><i>Moderate importance</i></td><td></td><td><i>Strong importance</i></td><td></td><td><i>Very strong</i></td><td></td><td><i>Extreme importance</i></td><td rowspan="2">Parameters</td></tr>
<tr><td>9:1</td><td>8:1</td><td>7:1</td><td>6:1</td><td>5:1</td><td>4:1</td><td>3:1</td><td>2:1</td><td>1:1</td><td>1:2</td><td>1:3</td><td>1:4</td><td>1:5</td><td>1:6</td><td>1:7</td><td>1:8</td><td>1:9</td></tr>
<tr><td>Time delay/ disruption</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>Additional cost</td></tr>
<tr><td>Time delay/ disruption</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>Quality damage (cargo/equipment)</td></tr>
<tr><td>Additional cost</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>Quality damage (cargo/equipment)</td></tr>
</table>

Appendix Five

Questionnaire on the assessment of key risk factors in maritime container supply chains

Dear Sir/Madam,

My name is Chengpeng Wan; I am currently pursuing a PhD degree at the Liverpool Logistics Offshore and Marine Research Institute (LOOM) in Liverpool John Moores University. My research topic in Chapter 4 is “Risk assessment of key risk factors in maritime container supply chains”, which intends to carry out an in-depth analysis of the crucial risk factors in maritime container supply chains from the aspects of occurrence likelihood, visibility of risk factors, consequence in terms of time delay/disruption, consequence in terms of financial loss/additional cost, and consequence in terms of quality damage.

I am writing to elicit your opinion as an executive in the whole process of the container maritime logistics with expert knowledge on risk assessment. Your participation is voluntary; however, your assistance would be greatly appreciated in making this a meaningful questionnaire. The information gathered in this survey will be treated in the strictest confidence, as this has always been the policy of the Liverpool John Moores University. This survey will take you about 10-15 minutes. This questionnaire is anonymous. Thus your response cannot be attributed to you or your company.

If you have any questions about this research, please contact me at +44-(0)777 087 3050, or by email at cpwan@whut.edu.cn, or my supervisor, Prof. Zaili Yang, by email z.yang@ljmu.ac.uk.

Please accept my thanks for your anticipated co-operation. If you wish to receive a copy of the research results, please email me at cpwan@whut.edu.cn.

Yours faithfully,

Chengpeng Wan,
PhD Candidate

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Background information

In the previous research, top five risk factors are identified in terms of the value of risk index, which are " fierce competition", "fluctuation of fuel price", "change of exchange rates", "unattractive markets", and "transportation of dangerous goods". These risk factors are identified as the key risk factors in a maritime container supply chain system, which will be further studied in this research.

These key risk factors are evaluated in details in terms of their occurrence likelihood, visibility, consequence in terms of time delay/disruption, consequence in terms of additional cost, and consequence in terms of quality damage. Explanations of linguistic grades of each risk parameter are shown in Table 1.

Table 1. Definitions of linguistic grades of each risk parameter

Parameter	**Linguistic grades**	**Definition**
Likelihood	*Low*	Occurs less than once per year
	Medium	Expected to occur every few months
	High	Expected to occur at least monthly
Visibility	*Low*	Impossible or difficult to be detected through intensive risk checks
	Medium	Possible to be detected through intensive risk checks
	High	Possible to be detected through regular risk checks
Delay/disruption	*Low*	A delay of less than 24 hours in total
	Medium	A delay but no more than 20% of the original schedule
	High	A delay of more than 20% of the original schedule
Additional cost	*Low*	An additional cost no more than 10% of the total cost
	Medium	An additional cost between 10% and 50% of the total cost
	High	An additional cost of more than 50% of the total cost
Quality damage	*Low*	Slight cargo, equipment, or system damage but fully functional and serviceable
	Medium	Minor incapability of systems or equipment and a small portion of goods may be damaged
	High	Damage/loss of major systems or equipment, and serious damage to the transported goods

For example (see Table 2):

Based on your experience, in which level do you think that "Fierce competition" **Likelihood** would be? How about the **visibility, delay/ disruption, additional cost/ financial loss,** and **quality damage (cargo/equipment)? It** is noted that the sum of belief degree on all selected grades in terms of each risk factor is less or equal to 1.

Then, please make your judgement for every risk factors in terms of each risk parameter based on your knowledge and experience in Table 3.

Table 2. Examples of judgement

Key risk factors	Risk parameters														
	1. Likelihood			2. Visibility			3. Consequence								
							3-1. Delay/ disruption			3-2. Additional cost/ Financial loss			3-3. Quality damage (cargo/equipment)		
	Low	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*
Fierce competition	0.2	0.3	0.5	0.1	0.1	0.8		0.8	0.2	0.1	0.9		0.2	0.2	0.6

Table 3. Assessment of key risk factors in terms of different risk parameters

Key risk factors	Risk parameters														
	1. Likelihood			2. Visibility			3. Consequence								
							3-1. Delay/ disruption			3-2. Additional cost			3-3. Quality damage (cargo/equipment)		
	Low	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*
Fierce competition															
Fluctuation of fuel price															
Change of exchange rates															
Unattractive markets															
Transportation of dangerous goods															

Appendix Six

Table 1. Belief Rule Base in MCSC Risk Assessment

Rules	**Antecedent attribute (input)**					**Risk result (output)**		
No	L	V	CT	CC	CQ	*Low*	*Medium*	*High*
1	Unlikely	Good	Low	Low	Negligible	1		
2	Unlikely	Good	Low	Low	Moderate	0.69	0.31	
3	Unlikely	Good	Low	Low	Critical	0.69		0.31
4	Unlikely	Good	Low	Medium	Negligible	0.92	0.08	
5	Unlikely	Good	Low	Medium	Moderate	0.61	0.39	
6	Unlikely	Good	Low	Medium	Critical	0.61	0.08	0.31
7	Unlikely	Good	Low	High	Negligible	0.92		0.08
8	Unlikely	Good	Low	High	Moderate	0.61	0.31	0.08
9	Unlikely	Good	Low	High	Critical	0.61		0.39
10	Unlikely	Good	Medium	Low	Negligible	0.65	0.35	
11	Unlikely	Good	Medium	Low	Moderate	0.34	0.66	
12	Unlikely	Good	Medium	Low	Critical	0.34	0.35	0.31
13	Unlikely	Good	Medium	Medium	Negligible	0.57	0.43	
14	Unlikely	Good	Medium	Medium	Moderate	0.26	0.74	
15	Unlikely	Good	Medium	Medium	Critical	0.26	0.43	0.31
16	Unlikely	Good	Medium	High	Negligible	0.57	0.35	0.08
17	Unlikely	Good	Medium	High	Moderate	0.26	0.66	0.08
18	Unlikely	Good	Medium	High	Critical	0.26	0.35	0.39
19	Unlikely	Good	High	Low	Negligible	0.65		0.35
20	Unlikely	Good	High	Low	Moderate	0.34	0.31	0.35
21	Unlikely	Good	High	Low	Critical	0.34		0.66
22	Unlikely	Good	High	Medium	Negligible	0.57	0.08	0.35
23	Unlikely	Good	High	Medium	Moderate	0.26	0.39	0.35
24	Unlikely	Good	High	Medium	Critical	0.26	0.08	0.66
25	Unlikely	Good	High	High	Negligible	0.57		0.43
26	Unlikely	Good	High	High	Moderate	0.26	0.31	0.43
27	Unlikely	Good	High	High	Critical	0.26		0.74
28	Unlikely	Normal	Low	Low	Negligible	0.92	0.08	
29	Unlikely	Normal	Low	Low	Moderate	0.61	0.39	
30	Unlikely	Normal	Low	Low	Critical	0.61	0.08	0.31
31	Unlikely	Normal	Low	Medium	Negligible	0.84	0.16	
32	Unlikely	Normal	Low	Medium	Moderate	0.53	0.47	
33	Unlikely	Normal	Low	Medium	Critical	0.53	0.16	0.31
34	Unlikely	Normal	Low	High	Negligible	0.84	0.08	0.08
35	Unlikely	Normal	Low	High	Moderate	0.53	0.39	0.08
36	Unlikely	Normal	Low	High	Critical	0.53	0.08	0.39
37	Unlikely	Normal	Medium	Low	Negligible	0.57	0.43	
38	Unlikely	Normal	Medium	Low	Moderate	0.26	0.74	
39	Unlikely	Normal	Medium	Low	Critical	0.26	0.43	0.31
40	Unlikely	Normal	Medium	Medium	Negligible	0.49	0.51	
41	Unlikely	Normal	Medium	Medium	Moderate	0.18	0.82	
42	Unlikely	Normal	Medium	Medium	Critical	0.18	0.51	0.31
43	Unlikely	Normal	Medium	High	Negligible	0.49	0.43	0.08
44	Unlikely	Normal	Medium	High	Moderate	0.18	0.74	0.08
45	Unlikely	Normal	Medium	High	Critical	0.18	0.43	0.39
46	Unlikely	Normal	High	Low	Negligible	0.57	0.08	0.35

47	Unlikely	Normal	High	Low	Moderate	0.26	0.39	0.35
48	Unlikely	Normal	High	Low	Critical	0.26	0.08	0.66
49	Unlikely	Normal	High	Medium	Negligible	0.49	0.16	0.35
50	Unlikely	Normal	High	Medium	Moderate	0.18	0.47	0.35
51	Unlikely	Normal	High	Medium	Critical	0.18	0.16	0.66
52	Unlikely	Normal	High	High	Negligible	0.49	0.08	0.43
53	Unlikely	Normal	High	High	Moderate	0.18	0.39	0.43
54	Unlikely	Normal	High	High	Critical	0.18	0.08	0.74
55	Unlikely	Poor	Low	Low	Negligible	0.92		0.08
56	Unlikely	Poor	Low	Low	Moderate	0.61	0.31	0.08
57	Unlikely	Poor	Low	Low	Critical	0.61		0.39
58	Unlikely	Poor	Low	Medium	Negligible	0.84	0.08	0.08
59	Unlikely	Poor	Low	Medium	Moderate	0.53	0.39	0.08
60	Unlikely	Poor	Low	Medium	Critical	0.53	0.08	0.39
61	Unlikely	Poor	Low	High	Negligible	0.84		0.16
62	Unlikely	Poor	Low	High	Moderate	0.53	0.31	0.16
63	Unlikely	Poor	Low	High	Critical	0.53		0.47
64	Unlikely	Poor	Medium	Low	Negligible	0.57	0.35	0.08
65	Unlikely	Poor	Medium	Low	Moderate	0.26	0.66	0.08
66	Unlikely	Poor	Medium	Low	Critical	0.26	0.35	0.39
67	Unlikely	Poor	Medium	Medium	Negligible	0.49	0.43	0.08
68	Unlikely	Poor	Medium	Medium	Moderate	0.18	0.74	0.08
69	Unlikely	Poor	Medium	Medium	Critical	0.18	0.43	0.39
70	Unlikely	Poor	Medium	High	Negligible	0.49	0.35	0.16
71	Unlikely	Poor	Medium	High	Moderate	0.18	0.66	0.16
72	Unlikely	Poor	Medium	High	Critical	0.18	0.35	0.47
73	Unlikely	Poor	High	Low	Negligible	0.57		0.43
74	Unlikely	Poor	High	Low	Moderate	0.26	0.31	0.43
75	Unlikely	Poor	High	Low	Critical	0.26		0.74
76	Unlikely	Poor	High	Medium	Negligible	0.49	0.08	0.43
77	Unlikely	Poor	High	Medium	Moderate	0.18	0.39	0.43
78	Unlikely	Poor	High	Medium	Critical	0.18	0.08	0.74
79	Unlikely	Poor	High	High	Negligible	0.49		0.51
80	Unlikely	Poor	High	High	Moderate	0.18	0.31	0.51
81	Unlikely	Poor	High	High	Critical	0.18		0.82
82	Occasional	Good	Low	Low	Negligible	0.82	0.18	
83	Occasional	Good	Low	Low	Moderate	0.51	0.49	
84	Occasional	Good	Low	Low	Critical	0.51	0.18	0.31
85	Occasional	Good	Low	Medium	Negligible	0.74	0.26	
86	Occasional	Good	Low	Medium	Moderate	0.43	0.57	
87	Occasional	Good	Low	Medium	Critical	0.43	0.26	0.31
88	Occasional	Good	Low	High	Negligible	0.74	0.18	0.08
89	Occasional	Good	Low	High	Moderate	0.43	0.49	0.08
90	Occasional	Good	Low	High	Critical	0.43	0.18	0.39
91	Occasional	Good	Medium	Low	Negligible	0.47	0.53	
92	Occasional	Good	Medium	Low	Moderate	0.16	0.84	
93	Occasional	Good	Medium	Low	Critical	0.16	0.53	0.31
94	Occasional	Good	Medium	Medium	Negligible	0.39	0.61	
95	Occasional	Good	Medium	Medium	Moderate	0.08	0.92	
96	Occasional	Good	Medium	Medium	Critical	0.08	0.61	0.31
97	Occasional	Good	Medium	High	Negligible	0.39	0.53	0.08
98	Occasional	Good	Medium	High	Moderate	0.08	0.84	0.08
99	Occasional	Good	Medium	High	Critical	0.08	0.53	0.39

100	Occasional	Good	High	Low	Negligible	0.47	0.18	0.35
101	Occasional	Good	High	Low	Moderate	0.16	0.49	0.35
102	Occasional	Good	High	Low	Critical	0.16	0.18	0.66
103	Occasional	Good	High	Medium	Negligible	0.39	0.26	0.35
104	Occasional	Good	High	Medium	Moderate	0.08	0.57	0.35
105	Occasional	Good	High	Medium	Critical	0.08	0.26	0.66
106	Occasional	Good	High	High	Negligible	0.39	0.18	0.43
107	Occasional	Good	High	High	Moderate	0.08	0.49	0.43
108	Occasional	Good	High	High	Critical	0.08	0.18	0.74
109	Occasional	Normal	Low	Low	Negligible	0.74	0.26	
110	Occasional	Normal	Low	Low	Moderate	0.43	0.57	
111	Occasional	Normal	Low	Low	Critical	0.43	0.26	0.31
112	Occasional	Normal	Low	Medium	Negligible	0.66	0.34	
113	Occasional	Normal	Low	Medium	Moderate	0.35	0.65	
114	Occasional	Normal	Low	Medium	Critical	0.35	0.34	0.31
115	Occasional	Normal	Low	High	Negligible	0.66	0.26	0.08
116	Occasional	Normal	Low	High	Moderate	0.35	0.57	0.08
117	Occasional	Normal	Low	High	Critical	0.35	0.26	0.39
118	Occasional	Normal	Medium	Low	Negligible	0.39	0.61	
119	Occasional	Normal	Medium	Low	Moderate	0.08	0.92	
120	Occasional	Normal	Medium	Low	Critical	0.08	0.61	0.31
121	Occasional	Normal	Medium	Medium	Negligible	0.31	0.69	
122	Occasional	Normal	Medium	Medium	Moderate		1	
123	Occasional	Normal	Medium	Medium	Critical		0.69	0.31
124	Occasional	Normal	Medium	High	Negligible	0.31	0.61	0.08
125	Occasional	Normal	Medium	High	Moderate		0.92	0.08
126	Occasional	Normal	Medium	High	Critical		0.61	0.39
127	Occasional	Normal	High	Low	Negligible	0.39	0.26	0.35
128	Occasional	Normal	High	Low	Moderate	0.08	0.57	0.35
129	Occasional	Normal	High	Low	Critical	0.08	0.26	0.66
130	Occasional	Normal	High	Medium	Negligible	0.31	0.34	0.35
131	Occasional	Normal	High	Medium	Moderate		0.65	0.35
132	Occasional	Normal	High	Medium	Critical		0.34	0.66
133	Occasional	Normal	High	High	Negligible	0.31	0.26	0.43
134	Occasional	Normal	High	High	Moderate		0.57	0.43
135	Occasional	Normal	High	High	Critical		0.26	0.74
136	Occasional	Poor	Low	Low	Negligible	0.74	0.18	0.08
137	Occasional	Poor	Low	Low	Moderate	0.43	0.49	0.08
138	Occasional	Poor	Low	Low	Critical	0.43	0.18	0.39
139	Occasional	Poor	Low	Medium	Negligible	0.66	0.26	0.08
140	Occasional	Poor	Low	Medium	Moderate	0.35	0.57	0.08
141	Occasional	Poor	Low	Medium	Critical	0.35	0.26	0.39
142	Occasional	Poor	Low	High	Negligible	0.66	0.18	0.16
143	Occasional	Poor	Low	High	Moderate	0.35	0.49	0.16
144	Occasional	Poor	Low	High	Critical	0.35	0.18	0.47
145	Occasional	Poor	Medium	Low	Negligible	0.39	0.53	0.08
146	Occasional	Poor	Medium	Low	Moderate	0.08	0.84	0.08
147	Occasional	Poor	Medium	Low	Critical	0.08	0.53	0.39
148	Occasional	Poor	Medium	Medium	Negligible	0.31	0.61	0.08
149	Occasional	Poor	Medium	Medium	Moderate		0.92	0.08
150	Occasional	Poor	Medium	Medium	Critical		0.61	0.39
151	Occasional	Poor	Medium	High	Negligible	0.31	0.53	0.16
152	Occasional	Poor	Medium	High	Moderate		0.84	0.16

153	Occasional	Poor	Medium	High	Critical		0.53	0.47
154	Occasional	Poor	High	Low	Negligible	0.39	0.18	0.43
155	Occasional	Poor	High	Low	Moderate	0.08	0.49	0.43
156	Occasional	Poor	High	Low	Critical	0.08	0.18	0.74
157	Occasional	Poor	High	Medium	Negligible	0.31	0.26	0.43
158	Occasional	Poor	High	Medium	Moderate		0.57	0.43
159	Occasional	Poor	High	Medium	Critical		0.26	0.74
160	Occasional	Poor	High	High	Negligible	0.31	0.18	0.51
161	Occasional	Poor	High	High	Moderate		0.49	0.51
162	Occasional	Poor	High	High	Critical		0.18	0.82
163	Frequent	Good	Low	Low	Negligible	0.82		0.18
164	Frequent	Good	Low	Low	Moderate	0.51	0.31	0.18
165	Frequent	Good	Low	Low	Critical	0.51		0.49
166	Frequent	Good	Low	Medium	Negligible	0.74	0.08	0.18
167	Frequent	Good	Low	Medium	Moderate	0.43	0.39	0.18
168	Frequent	Good	Low	Medium	Critical	0.43	0.08	0.49
169	Frequent	Good	Low	High	Negligible	0.74		0.26
170	Frequent	Good	Low	High	Moderate	0.43	0.31	0.26
171	Frequent	Good	Low	High	Critical	0.43		0.57
172	Frequent	Good	Medium	Low	Negligible	0.47	0.35	0.18
173	Frequent	Good	Medium	Low	Moderate	0.16	0.66	0.18
174	Frequent	Good	Medium	Low	Critical	0.16	0.35	0.49
175	Frequent	Good	Medium	Medium	Negligible	0.39	0.43	0.18
176	Frequent	Good	Medium	Medium	Moderate	0.08	0.74	0.18
177	Frequent	Good	Medium	Medium	Critical	0.08	0.43	0.49
178	Frequent	Good	Medium	High	Negligible	0.39	0.35	0.26
179	Frequent	Good	Medium	High	Moderate	0.08	0.66	0.26
180	Frequent	Good	Medium	High	Critical	0.08	0.35	0.57
181	Frequent	Good	High	Low	Negligible	0.47		0.53
182	Frequent	Good	High	Low	Moderate	0.16	0.31	0.53
183	Frequent	Good	High	Low	Critical	0.16		0.84
184	Frequent	Good	High	Medium	Negligible	0.39	0.08	0.53
185	Frequent	Good	High	Medium	Moderate	0.08	0.39	0.53
186	Frequent	Good	High	Medium	Critical	0.08	0.08	0.84
187	Frequent	Good	High	High	Negligible	0.39		0.61
188	Frequent	Good	High	High	Moderate	0.08	0.31	0.61
189	Frequent	Good	High	High	Critical	0.08		0.92
190	Frequent	Normal	Low	Low	Negligible	0.74	0.08	0.18
191	Frequent	Normal	Low	Low	Moderate	0.43	0.39	0.18
192	Frequent	Normal	Low	Low	Critical	0.43	0.08	0.49
193	Frequent	Normal	Low	Medium	Negligible	0.66	0.16	0.18
194	Frequent	Normal	Low	Medium	Moderate	0.35	0.47	0.18
195	Frequent	Normal	Low	Medium	Critical	0.35	0.16	0.49
196	Frequent	Normal	Low	High	Negligible	0.66	0.08	0.26
197	Frequent	Normal	Low	High	Moderate	0.35	0.39	0.26
198	Frequent	Normal	Low	High	Critical	0.35	0.08	0.57
199	Frequent	Normal	Medium	Low	Negligible	0.39	0.43	0.18
200	Frequent	Normal	Medium	Low	Moderate	0.08	0.74	0.18
201	Frequent	Normal	Medium	Low	Critical	0.08	0.43	0.49
202	Frequent	Normal	Medium	Medium	Negligible	0.31	0.51	0.18
203	Frequent	Normal	Medium	Medium	Moderate		0.82	0.18
204	Frequent	Normal	Medium	Medium	Critical		0.51	0.49
205	Frequent	Normal	Medium	High	Negligible	0.31	0.43	0.26

206	Frequent	Normal	Medium	High	Moderate		0.74	0.26
207	Frequent	Normal	Medium	High	Critical		0.43	0.57
208	Frequent	Normal	High	Low	Negligible	0.39	0.08	0.53
209	Frequent	Normal	High	Low	Moderate	0.08	0.39	0.53
210	Frequent	Normal	High	Low	Critical	0.08	0.08	0.84
211	Frequent	Normal	High	Medium	Negligible	0.31	0.16	0.53
212	Frequent	Normal	High	Medium	Moderate		0.47	0.53
213	Frequent	Normal	High	Medium	Critical		0.16	0.84
214	Frequent	Normal	High	High	Negligible	0.31	0.08	0.61
215	Frequent	Normal	High	High	Moderate		0.39	0.61
216	Frequent	Normal	High	High	Critical		0.08	0.92
217	Frequent	Poor	Low	Low	Negligible	0.74		0.26
218	Frequent	Poor	Low	Low	Moderate	0.43	0.31	0.26
219	Frequent	Poor	Low	Low	Critical	0.43		0.57
220	Frequent	Poor	Low	Medium	Negligible	0.66	0.08	0.26
221	Frequent	Poor	Low	Medium	Moderate	0.35	0.39	0.26
222	Frequent	Poor	Low	Medium	Critical	0.35	0.08	0.57
223	Frequent	Poor	Low	High	Negligible	0.66		0.34
224	Frequent	Poor	Low	High	Moderate	0.35	0.31	0.34
225	Frequent	Poor	Low	High	Critical	0.35		0.65
226	Frequent	Poor	Medium	Low	Negligible	0.39	0.35	0.26
227	Frequent	Poor	Medium	Low	Moderate	0.08	0.66	0.26
228	Frequent	Poor	Medium	Low	Critical	0.08	0.35	0.57
229	Frequent	Poor	Medium	Medium	Negligible	0.31	0.43	0.26
230	Frequent	Poor	Medium	Medium	Moderate		0.74	0.26
231	Frequent	Poor	Medium	Medium	Critical		0.43	0.57
232	Frequent	Poor	Medium	High	Negligible	0.31	0.35	0.34
233	Frequent	Poor	Medium	High	Moderate		0.66	0.34
234	Frequent	Poor	Medium	High	Critical		0.35	0.65
235	Frequent	Poor	High	Low	Negligible	0.39		0.61
236	Frequent	Poor	High	Low	Moderate	0.08	0.31	0.61
237	Frequent	Poor	High	Low	Critical	0.08		0.92
238	Frequent	Poor	High	Medium	Negligible	0.31	0.08	0.61
239	Frequent	Poor	High	Medium	Moderate		0.39	0.61
240	Frequent	Poor	High	Medium	Critical		0.08	0.92
241	Frequent	Poor	High	High	Negligible	0.31		0.69
242	Frequent	Poor	High	High	Moderate		0.31	0.69
243	Frequent	Poor	High	High	Critical			1

Appendix Seven

Table 1. Normalised centrality values and overall scores of all ports

Port	$\mathbf{C}'_{\boldsymbol{D}}(\boldsymbol{i})$	$\mathbf{C}'_{\boldsymbol{C}}(\boldsymbol{i})$	$\mathbf{C}'_{\boldsymbol{B}}(\boldsymbol{i})$	$\boldsymbol{S_O}(\boldsymbol{i})$
Xingang	0.1635	0.5538	0.0086	189.621
Qingdao	0.4052	0.6573	0.0699	207.348
Shanghai	0.5711	0.8023	0.1560	211.657
Dalian	0.1422	0.5452	0.0069	185.93
Ningbo	0.4265	0.7701	0.0349	208.268
Yantian	0.2938	0.6394	0.0458	205
Shekou	0.2844	0.6394	0.0176	201.239
Chiwan	0.1564	0.5275	0.0092	186.093
Fuqing	0.0284	0.4480	0.0000	59.595
Hong Kong	0.4194	0.6873	0.0794	209.343
Xiamen	0.2678	0.6280	0.0312	202.326
Nansha	0.2156	0.5960	0.0317	200.693
Yantai	0.0095	0.4154	0.0000	37.457
Zhanjiang	0.0213	0.4170	0.0000	48.345
Taipei	0.0853	0.5249	0.0005	152.226
Busan	0.3839	0.6785	0.0728	207.681
Incheon	0.0474	0.4817	0.0098	141.361
Kwangyang	0.0355	0.4785	0.0002	100.041
Lianyungang	0.0640	0.4795	0.0011	130.526
Kaohsiung	0.2701	0.6063	0.0267	201.988
Prince Rupert	0.0379	0.4763	0.0000	91.484
Long Beach	0.0758	0.4817	0.0007	135.333
Oakland	0.0782	0.4862	0.0009	141.299
Seattle	0.0427	0.4720	0.0000	93.636
Tokyo	0.1043	0.4896	0.0089	167.375
Cai Mep	0.1303	0.5288	0.0031	176.87
Tacoma	0.0332	0.4710	0.0000	81.719
Singapore	0.5450	0.7456	0.1608	211.017
Port Klang	0.3957	0.6763	0.0693	207
Jakarta	0.0616	0.4699	0.0006	113.357
Laem Chabang	0.1161	0.5121	0.0027	167.963
Los Angeles	0.0261	0.4607	0.0000	57.212
Colombo	0.1706	0.5672	0.0066	190.181
Vancouver	0.0569	0.4806	0.0003	117.945
Yokohama	0.1137	0.4953	0.0065	169.215
Osaka	0.0687	0.4828	0.0031	145.011
Colon	0.0498	0.4752	0.0002	105.341
Savannah	0.0687	0.4839	0.0004	129.199
Charleston	0.0403	0.4720	0.0000	89.947
New York	0.0900	0.4884	0.0013	149
Boston	0.0332	0.4752	0.0000	83.111
Cape of Good Hope	0.0427	0.4774	0.0002	104.666
Norfolk	0.0782	0.4884	0.0013	145.004
Panama Canal	0.0877	0.4896	0.0016	150.345

Suez Canal	0.0829	0.4907	0.0010	146.25
Baltimore	0.0237	0.4423	0.0000	51.294
Halifax	0.0355	0.4637	0.0000	70.106
Houston	0.0379	0.4774	0.0001	98.979
Mobile	0.0379	0.4774	0.0001	98.979
New Orleans	0.0284	0.4689	0.0000	68.02
Miami	0.0284	0.4689	0.0000	68.02
Jacksonville	0.0284	0.4689	0.0000	68.02
Rotterdam	0.2251	0.5765	0.0615	201.406
Felixstowe	0.1422	0.5452	0.0196	191.761
Gdansk	0.0403	0.4918	0.0024	131.921
Wilhelmshaven	0.0284	0.4896	0.0000	88.884
Algeciras	0.1256	0.5342	0.0108	185.778
Southampton	0.1019	0.5369	0.0033	174.888
Dunkerque	0.0829	0.5262	0.0037	168.344
Hamburg	0.1706	0.5672	0.0090	192.925
Zeebrugge	0.0379	0.5084	0.0000	106.001
Le Havre	0.1161	0.5410	0.0065	181.275
Khor Fakkan	0.1635	0.5642	0.0091	191.954
Piraeus	0.2488	0.5910	0.0242	200.331
Antwerp	0.1825	0.5734	0.0042	188.78
Malta	0.1374	0.5495	0.0042	183.193
Jeddah	0.2180	0.5813	0.0180	197.971
Tanjung Pelepas	0.0948	0.5262	0.0014	163.067
La Spezia	0.0687	0.5159	0.0002	137.882
Genoa	0.1445	0.5424	0.0185	191.097
Valencia	0.1114	0.5383	0.0044	178.265
Fos	0.0972	0.5275	0.0020	166.096
Barcelona	0.0711	0.5060	0.0002	137.238
Beirut	0.0972	0.5262	0.0022	166.473
Jebel Ali	0.1967	0.5642	0.0137	194.993
Port Said	0.1185	0.5197	0.0036	173.989
Izmit	0.0711	0.5024	0.0008	145.144
Ambarli	0.0450	0.4884	0.0000	106.183
Constantza	0.0545	0.4930	0.0032	145.602
Odessa	0.0427	0.4884	0.0000	102.801
Mersin	0.1137	0.5355	0.0036	176.56
Ashdod	0.0640	0.5084	0.0060	157.218
Haifa	0.0782	0.5302	0.0028	166.225
Alexandria	0.0592	0.5184	0.0005	140.697
Koper	0.0735	0.4953	0.0076	161.331
Trieste	0.0403	0.4785	0.0000	92.008
Rijeka	0.0545	0.4907	0.0018	138.107
Venice	0.0616	0.4953	0.0024	145.781
Damietta	0.1066	0.5210	0.0020	165.824
Port Qasim	0.0782	0.4113	0.0022	114.255
Nhava Sheva	0.1303	0.5612	0.0080	187.282
Hazira	0.0332	0.3922	0.0000	56.705

Mundra	0.1374	0.5612	0.0064	185.2
King Abdullah	0.0521	0.3922	0.0004	87.059
Gioia Tauro	0.0355	0.3922	0.0000	59.022
Tangier	0.0877	0.4237	0.0016	118.414
Djibouti	0.0853	0.5236	0.0026	164.591
Cagliari	0.0545	0.4137	0.0003	90.619
London Gateway	0.0592	0.4203	0.0004	96.225
Dammam	0.0735	0.5097	0.0020	153.615
Jubail	0.0640	0.5000	0.0013	144.955
Kumport	0.0545	0.4129	0.0005	93.037
Aliaga	0.0355	0.3951	0.0000	60.652
Iskenderun	0.0355	0.3951	0.0000	60.652
Karachi	0.1161	0.5288	0.0024	171.773
Izmir	0.0640	0.4170	0.0012	106.093
St. Petersburg	0.0190	0.3748	0.0000	36.634
Kotka	0.0190	0.3748	0.0000	36.634
Dublin	0.0047	0.3663	0.0000	26.022
Oslo	0.0095	0.3676	0.0000	28.655
Helsingborg	0.0095	0.3676	0.0000	28.655
Gothenburg	0.0095	0.3676	0.0000	28.655
Ravenna	0.0142	0.3768	0.0000	33.575
Ancona	0.0190	0.3775	0.0000	36.875
Gemlik	0.0190	0.3775	0.0000	36.875
Thessaloniki	0.0284	0.3802	0.0003	62.815
Novorossiysk	0.0142	0.3748	0.0000	32.271
Varna	0.0142	0.3748	0.0000	32.271
Istanbul	0.0142	0.3748	0.0000	32.271
Napoli	0.0118	0.3657	0.0000	28.013
Gebze	0.0213	0.3937	0.0000	43.781
Salerno	0.0213	0.3937	0.0000	43.781
Casablanca	0.0308	0.3974	0.0000	59.798
Melbourne	0.0592	0.4742	0.0007	120.587
Sydney	0.0592	0.4742	0.0007	120.587
Brisbane	0.0948	0.4907	0.0025	157.437
Adelaide	0.0237	0.4369	0.0000	54.741
Fremantle	0.0213	0.4324	0.0000	51.724
Kobe	0.0427	0.4785	0.0000	97.755
Oakland	0.0521	0.4817	0.0004	121.323
Lyttelton	0.0521	0.4817	0.0003	119.265
Napier	0.0521	0.4817	0.0003	118.922
Tauranga	0.0521	0.4817	0.0003	118.922
Port Chalmers	0.0261	0.4658	0.0000	60.472
Wellington	0.0213	0.4369	0.0000	49.975
Bahrain	0.0261	0.4720	0.0000	69.6
Hamad	0.0237	0.4678	0.0000	59.118
Khalifa Port	0.0427	0.4839	0.0001	107.739
Sohar	0.0332	0.4731	0.0000	80.177
Bandar Abbas	0.0355	0.4731	0.0000	82.837

Sokhna	0.0261	0.4689	0.0000	64.71
Aqaba	0.0379	0.4795	0.0000	97.831
Port Sudan	0.0261	0.4763	0.0000	74.164
Durban	0.0308	0.4648	0.0000	68.532
Keelung	0.0521	0.4752	0.0096	137.818
Apapa	0.0782	0.5000	0.0030	158.435
Tin Can	0.0521	0.4851	0.0001	115.03
Cotonou	0.0521	0.4851	0.0001	115.373
Tema	0.0711	0.4965	0.0030	153.804
Cape Town	0.0498	0.4828	0.0001	112.822
Lome	0.0782	0.5024	0.0024	157.029
Onne	0.0355	0.4795	0.0000	89.34
Walvis Bay	0.0332	0.4806	0.0000	87.675
Abidjan	0.0735	0.5134	0.0072	164.557
Pointe Noire	0.0308	0.4720	0.0000	76.22
Luanda	0.0308	0.4720	0.0000	76.22
Castellon	0.0261	0.3768	0.0000	44.498
Dakar	0.0450	0.3929	0.0006	86.512
Lagos	0.0284	0.3768	0.0000	47.808
Takoradi	0.0284	0.3768	0.0000	47.808
Tilbury	0.0332	0.3781	0.0005	74.266
Tanger Med	0.0190	0.3781	0.0000	37.527
Mombasa	0.0427	0.4731	0.0001	97.701
Dar es Salaam	0.0332	0.4720	0.0000	84.344
Pasir Gudang	0.0261	0.4710	0.0000	67.318
Itaguai	0.0308	0.4742	0.0000	79.154
Santos	0.0948	0.5184	0.0013	159.756
Paranagua	0.0900	0.5184	0.0011	157.391
Navegantes	0.0427	0.4742	0.0000	91.425
Montevideo	0.0853	0.5184	0.0010	155.381
Buenos Aires	0.0853	0.5184	0.0010	155.381
Rio Grande	0.0379	0.4742	0.0000	86.767
Sepetiba	0.0569	0.4678	0.0000	95.437
Imbituba	0.0450	0.4678	0.0000	81.957
Itajai	0.0450	0.4678	0.0000	81.957
Itapoa	0.0664	0.5000	0.0004	138.071
Manzanillo	0.0995	0.4930	0.0018	155.978
Buenaventura	0.0711	0.4817	0.0004	130.579
Callao	0.0711	0.4817	0.0005	132.294
Cardenas	0.0308	0.4648	0.0000	65.788
Puerto Quetzal	0.0308	0.4648	0.0000	65.788
Guayaquil	0.0545	0.4699	0.0001	101.448
Iquique	0.0261	0.4699	0.0000	66.014
Valparaiso	0.0261	0.4699	0.0000	66.014
Lazaro Cardenas	0.0640	0.4710	0.0002	109.101
Balboa	0.0664	0.4710	0.0002	110.449
San Antonio	0.0403	0.4658	0.0000	76.36
Lirquen	0.0403	0.4658	0.0000	76.36

Ensenada	0.0498	0.4742	0.0001	101.276
Cartagena	0.0308	0.4689	0.0000	71.33
Kingston	0.0308	0.4689	0.0000	71.33
Caucedo	0.0308	0.4689	0.0000	71.33
Sihanoukville	0.0166	0.4547	0.0000	45.973
Bangkok	0.0284	0.4678	0.0000	71.226
Nagoya	0.0332	0.4597	0.0000	73.362
Moji	0.0213	0.4499	0.0000	51.605
Haiphong	0.0332	0.4678	0.0000	78.544
Ho Chi Minh	0.0640	0.4953	0.0073	156.685
Fangchenggang	0.0379	0.4170	0.0235	110.099
Qinzhou	0.0213	0.4170	0.0000	48.345
Yangpu	0.0213	0.4170	0.0000	48.345
Gaolan	0.0213	0.4170	0.0000	48.345
Humen	0.0213	0.4170	0.0000	48.345
Da Nang	0.0166	0.4607	0.0000	46.951
Jiangyin	0.0521	0.4851	0.0001	117.088
Vizag	0.0261	0.4617	0.0000	57.864
Manila	0.0213	0.4617	0.0000	53.561
Penang	0.0213	0.4720	0.0000	65.297
Pipavav	0.0284	0.4795	0.0000	80.734
Dafeng	0.0095	0.4480	0.0000	42.347
Daesan	0.0118	0.4499	0.0000	43.661
Shantou	0.0190	0.4658	0.0000	52.197

Appendix Eight

Questionnaire on the operational risk assessment of maritime container supply chains

Dear Sir/Madam,

My name is Chengpeng Wan; I am currently pursuing a PhD degree at the Liverpool Logistics Offshore and Marine Research Institute (LOOM) in Liverpool John Moores University. My research topic in Chapter 6 is “An integrated approach for comprehensive safety evaluation of MCSCs from a systematic perspective”, in which a case study of maritime container supply chains related to the Africa region is carried to illustrate the practicality of the proposed method in the safety evaluation. In the survey, 26 identified operational risk factors would be assessed in terms of their occurrence likelihood, visibility, and consequence associated with time delay/disruption, financial loss/additional cost, as well as quality damage.

I am writing to elicit your opinion as an executive in the whole process of the container maritime logistics with expert knowledge on risk assessment. Your participation is voluntary; however, your assistance would be greatly appreciated in making this a meaningful questionnaire. The information gathered in this survey will be treated in the strictest confidence, as this has always been the policy of the Liverpool John Moores University. This survey will take you about 15-20 minutes. This questionnaire is anonymous. Thus your response cannot be attributed to you or your company.

If you have any questions about this research, please contact me at +44-(0)777 087 3050, or by email at cpwan@whut.edu.cn, or my supervisor, Prof. Zaili Yang, by email z.yang@ljmu.ac.uk.

Please accept my thanks for your anticipated co-operation. If you wish to receive a copy of the research results, please email me at cpwan@whut.edu.cn.

Yours faithfully,

Chengpeng Wan,
PhD Candidate

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Background information

There are altogether 26 risk factors related to the operational aspect of maritime container supply chains, and they will be evaluated in details in terms of their occurrence likelihood, visibility, consequence in terms of time delay/disruption, consequence in terms of additional cost, and consequence in terms of quality damage. Explanations of linguistic grades of each risk parameter are shown in Table 1.

Table 1. Definitions of linguistic grades of each risk parameter

Parameter	**Linguistic grades**	**Definition**
Likelihood	*Low*	Occurs less than once per year
	Medium	Expected to occur every few months
	High	Expected to occur at least monthly
Visibility	*Low*	Impossible or difficult to be detected through intensive risk checks
	Medium	Possible to be detected through intensive risk checks
	High	Possible to be detected through regular risk checks
Delay/disruption	*Low*	A delay of less than 24 hours in total
	Medium	A delay but no more than 20% of the original schedule
	High	A delay of more than 20% of the original schedule
Additional cost	*Low*	An additional cost no more than 10% of the total cost
	Medium	An additional cost between 10% and 50% of the total cost
	High	An additional cost of more than 50% of the total cost
Quality damage	*Low*	Slight cargo, equipment, or system damage but fully functional and serviceable
	Medium	Minor incapability of systems or equipment and a small portion of goods may be damaged
	High	Damage/loss of major systems or equipment, and serious damage to the transported goods

Based on your knowledge and experience, please make your judgement for each risk factor in terms of the given risk parameters in Table 2.

Table 2. Assessment of operational risks of maritime container supply chains

Operational risk	**Risk parameters**														
Risk factors related to **Information flow**	**Likelihood**			**Visibility**			**Consequence**								
							Delay/ disruption			**Additional cost**			**Quality damage (cargo/equipment)**		
	Low	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*
1. Information delay															
2. Information inaccuracy															
3. IT vulnerability															
4. Internet security															
5. Poor information sharing															
6. Lack of information standardisation and compatibility															
Risk factors related to **financial flow**	*Low*	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*
7. Payment delay from partners															
8. Break a contract															
9. Shippers going into bankruptcy															
10. Partners with bad credit															
11. Charter rates rise															

12. Cash flow problem															
Risk factors related to **physical flow**	*Low*	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*	*Low*	*Med*	*High*
13. Inaccurate demand forecast															
14. Transportation of dangerous goods															
15. Container shortage															
16. Port strikes															
17. Port/ terminal congestions															
18. Lack of flexibility of designed schedules															
19. Problems with customs clearance															
20. Electricity failure															
21. Bottlenecks/restriction on transportation routes															
22. Improper container terminal operations															
23. Incorrect container packing															
24. Transport accidents															
25. Trade imbalance on container shipping routes															
26. Improper management of container storage area															

Appendix Nine

Examples of performing the ER algorithm

Suppose the risk factors "information delay" and "information inaccuracy" are represented as R_1 and R_2, respectively. Their risk status is expressed as:

$$R_1 = \{(Low, 0.63), (Medium, 0.31), (High, 0.06)\}$$

$$R_1 = \{(Low, 0.65, (Medium, 0.34), (High, 0.01)\}$$

And the relative weights of the two risk factors are:

$$w_1 = \frac{0.173}{0.173+0.181} = 0.49$$

$$w_2 = \frac{0.181}{0.173+0.181} = 0.51$$

Then, the synthesised risk status of the two risk factors can be calculated as follows:

According to Eqs. 6.8 and 6.9:

$$M_1^1 = w_1\beta_1^1 = 0.49 \times 0.63 = 0.3087$$

$$M_1^2 = w_1\beta_1^2 = 0.49 \times 0.31 = 0.1519$$

$$M_1^3 = w_1\beta_1^3 = 0.49 \times 0.06 = 0.0294$$

$$M_2^1 = w_2\beta_2^1 = 0.51 \times 0.65 = 0.3315$$

$$M_2^2 = w_2\beta_2^2 = 0.51 \times 0.34 = 0.1734$$

$$M_2^3 = w_2\beta_2^3 = 0.51 \times 0.01 = 0.0051$$

According to Eqs. 6.10 to 6.15:

$$\bar{H}_1 = 1 - w_1 = 1 - 0.49 = 0.51$$

$$\bar{H}_2 = 1 - w_2 = 1 - 0.51 = 0.49$$

$$\tilde{H}_1 = w_1\left(1 - \sum_{m=1}^{3} \beta_1^m\right) = 0.49 \times (1 - 0.63 - 0.31 - 0.06) = 0$$

$$\tilde{H}_2 = w_2\left(1 - \sum_{m=1}^{3} \beta_2^m\right) = 0.51 \times (1 - 0.65 - 0.34 - 0.01) = 0$$

$$H_1 = \bar{H}_1 + \tilde{H}_1 = 0.51 + 0 = 0.51$$

$$H_2 = \bar{H}_2 + \tilde{H}_2 = 0.49 + 0 = 0.49$$

According to Eq. 6.19:

$$K=\left(1-\sum_{s=1}^{3}\sum_{\substack{t=1\\t\neq s}}^{3}M_1^sM_2^t\right)^{-1}=\left(1-M_1^1M_2^2-M_1^1M_2^3-M_1^2M_2^1-M_1^2M_2^3-M_1^3M_2^1-M_1^3M_2^2\right)^{-1}$$

$$=(1-0.3087\times0.1734-0.3087\times0.0051-0.1519\times0.3315-0.1519\times0.0051-$$
$$0.0294\times0.3315-0.0294\times0.1734)^{-1}$$
$$=1.1378$$

According to Eqs. 6.16 to 6.18:

$$\beta^{1'}=K(M_1^1M_2^1+M_1^1H_2+M_2^1H_1)$$
$$=1.1378\times(0.3087\times0.3315+0.3087\times0.49+0.3315\times0.49)$$
$$=0.4809$$

$$\beta^{2'}=K(M_1^2M_2^2+M_1^2H_2+M_2^2H_1)$$
$$=1.1378\times(0.1519\times0.1734+0.1519\times0.49+0.1734\times0.49)$$
$$=0.2153$$

$$\beta^{3'}=K(M_1^3M_2^3+M_1^3H_2+M_2^3H_1)$$
$$=1.1378\times(0.0294\times0.0051+0.0294\times0.49+0.0051\times0.49)$$
$$=0.0195$$

$$\bar{H}_U^{'}=K(\bar{H}_1\bar{H}_2)=1.1378\times(0.51\times0.49)=0.2843$$

$$\tilde{H}_U^{'}=K(\tilde{H}_1\tilde{H}_2+\tilde{H}_1\bar{H}_2+\tilde{H}_2\bar{H}_1)=0$$

Finally, the normalised combined DoBs of risk factors 1 and 2 can be obtained using Eqs. 6.20 and 6.21.

$$\beta^1=\frac{\beta^{1'}}{1-\bar{H}_U^{'}}=\frac{0.4809}{1-0.2843}=0.6719$$

$$\beta^2=\frac{\beta^{2'}}{1-\bar{H}_U^{'}}=\frac{0.2153}{1-0.2843}=0.3008$$

$$\beta^1=\frac{\beta^{1'}}{1-\bar{H}_U^{'}}=\frac{0.0195}{1-0.2843}=0.0273$$

$H_U=\dfrac{\tilde{H}_U^{'}}{1-\bar{H}_U^{'}}=0$ (which means that the risk estimations of R_1 and R_2 are complete)

Therefore, the combined results of estimations on R_1 and R_2 can be expressed as:

$$R=\{(Low,0.672),(Medium,0.301),(High,0.027)\}$$

Appendix Ten

Research Deliverables Arising from this Research

[1] **Wan, C.,** Yang, Z., Zhang, D. et al. (2018). Resilience in transportation systems: a systematic review and future directions. *Transport Reviews*, 38(4), 479-498.

[2] **Wan, C.,** Wu, J. and Zhang, D. (2017). Data collection and analysis of container shipping networks on the 21st-Century Maritime Silk Road – A preliminary research. *Workshop on Global Perspectives of Belt and Road Initiative: Maritime Studies and China's Global Investment*, Zhou Shan, China.

[3] Zhang, D., Wu, J. and **Wan, C.*** (2018). Study on the comprehensive importance evaluation of ports along the Maritime Silk Road. *Journal of Transport Information and Safety (*under review, in Chinses*).*

[4] Wu, J., Zhang, D., **Wan C.*** et al. (2018). A novel approach for comprehensive centrality assessment of ports along the Maritime Silk Road. *Transportation Research Board 98th Annual Meeting* (No. 19-01623): Washington D.C., U.S. (Accepted)

[5] **Wan, C.,** Yan, X. Zhang, D. and Yang, Z. (2018). Analysis of risk factors influencing the safety of maritime container supply chains. *International Journal of Shipping and Transport Logistics* (in press).

[6] **Wan, C.,** Yan, X. Zhang, D., Qu, Z. and Yang, Z. (2018). An advanced fuzzy belief rule-based Bayesian network approach for maritime supply chain risk analysis. *Transportation Research Part E: Logistics and Transportation Review* (revision).

[7] **Wan, C.,** Yang, Z., Yan, X. and Zhang, D. (2019). Incorporating the safety evaluation into the importance measurement of maritime container supply chains – from a systematic perspective. *Reliability Engineering and System Safety* (to be submitted).

In Chapter 2, the research related to the definition and characteristics of the maritime transportation resilience and the methods widely applied in this field are comprehensively discussed, which provides the main structure and content for publication [1] (A literature review paper).

Chapter 3 proposes a novel framework for the classification of risk factors of maritime container supply chains (MCSCs) and screens the identified risk factors using a risk matrix method, which contributes to publication [4].

Chapter 4 performs an effective and efficient risk assessment of the major risk factors of MCSCs by combining the fuzzy rule base and Bayesian network in a complementary manner, which contributes to publication [5].

In Chapter 5, the method on how to construct a database for network analysis of global container liner networks is used in publication [2], while the newly proposed multi-centrality indicator which is used to measure the importance of ports in maritime container transportation networks contributes to publication [3].

Chapter 6 develops an integrated framework for facilitating safety evaluation of MCSCs from a systematic perspective by considering both the local risk condition of an MCSC and its global impact on the resilience of the entire maritime container supply network, contributing to publication [6].