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Abstract

This paper aims to develop a novel model to assess the risk factors of maritime supply chains by incorporating a fuzzy belief rule approach with Bayesian networks. The new model, compared to traditional risk analysis methods, has the capability of improving result accuracy under a high uncertainty in risk data. A real case of a world leading container shipping company is investigated, and the research results reveal that among the most significant risk factors are transportation of dangerous goods, fluctuation of fuel price, fierce competition, unattractive markets, and change of exchange rates in sequence. Such findings will provide useful insights for accident prevention.

Keywords: maritime supply chain, maritime transport, Bayesian network, fuzzy logic, FMEA, maritime risk

1 Introduction

The maritime industry is playing an increasingly important role in international trade as ships are carrying a large quantity of cargos over a long distance in a cost-effective and environmentally friendly manner (Rodrigue, 2017). This contributes to the fast development of maritime supply chains (MSCs). The UNCTAD report (2017) revealed that more than 80% of global trade in terms of volume is transported by ships. As a core component of the global logistics system, MSCs connect different transport modes to realise door-to-door services. Due to the high capital intensive characteristic of the maritime industry, any form of disruption along MSCs can adversely affect business sustainability and cause unimaginable losses. Furthermore, the impact will be passed onto other relevant transport modes along the same chain. For example, United States (U.S.) port labour disputes, leading to an 11-day lockout in 2002 and the shutdown of West Coast ports in 2005, caused a loss of $1 billion and $1.9 billion per day, respectively (Gorman, 2015). Thus, attention has been attracted from both academia and industry on how to properly and effectively analyse and manage risks associated with MSCs (Vilko and Hallikas, 2012; IMO, 2012), particularly taking into account the fact that many of them are from different perspectives and having various risk characteristics.

Numerous methods have been developed and applied in previous studies for supply chain risk management. They can be broadly classified into two groups, which are traditional risk analysis tools including risk matrix (Anthony, 2008), risk maps (Chang et al., 2015), the analytic hierarchy process (AHP) method (Asgari et al., 2015), the failure mode, effect analysis (FMEA) (Pujawan and Geraldin, 2009), and fault tree analysis (FTA) (Chen et al., 2011); and advanced uncertainty modelling techniques such as fuzzy logic, Monte Carlo simulation, and Dempster-Shafer theory (Liu et al., 2013c). However, these methods under many circumstances have shown inherent drawbacks/incapability in their practical applications. For example, AHP and FMEA cannot deal with the high uncertainties (e.g. incompleteness and vagueness) existing in risk data of supply chain operations, and D-S theory suffers from the conflict problems of evidence, which will lead to irrational results. Moreover, current research of supply chain risk management focuses more on only two risk parameters, (i.e. likelihood and consequence) and it is often studied from a single dimension such as financial, operational and technical. This will not provide enough information needed for decision making, and the situation is getting even worse with the increase of the global MSC complexity.

Therefore, several questions arise: What risk parameters need to be considered in the MSC risk assessment? How to provide a uniformed scale to measure the risks from different perspectives? How to utilize the selected risk parameters for accurate risk analysis in a rational way? How to deal with the uncertainties in the complex MSC systems? How can we make better use of the existing risk analysis tools in order to achieve a more flexible and accurate risk assessment? This paper attempts to answer these questions and fill in the research gaps by meeting the following research objectives:

(1) To determine the risk parameters influencing MSC risk analysis.

(2) To develop a suitable model for risk assessment of MSCs in an uncertain environment.

(3) To verify the rationality and feasibility of the proposed method.

This study provides a reference for both researchers and practitioners in terms of the assessment of risk factors under uncertainty. It provides a basis for evaluating different kinds of risks to ensure that the safety and security of maritime logistic systems can be tackled in an integrated framework. The novelty of this paper is threefold. Firstly, it systemically identifies the risk events relating to MSCs from a whole supply chain perspective involving multiple dimensions such as technical, operational, managerial and financial risks. Secondly, the study explores and incorporates more risk parameters, which is beneficial to better understanding and modelling of risks in MSCs. Thirdly, it develops a new method to effectively deal with different types of uncertainties existing in the risk assessment of MSC risks.

After the introduction, the next section reviews the related literature and highlights the research gaps. Section 3 presents the novel approach and steps for conducting an MSC risk assessment. In Section 4, the feasibility and superiority of the proposed method are demonstrated through a case study of a container shipping company. The main contributions of this study are discussed in Section 5, and this work is concluded in Section 6.

2 Literature review

Scholars have spent a lot of efforts in exploring, investigating, and evaluating MSC risks due to its importance in ensuring the safety and resilience of global maritime logistics systems. This section reviews the previous work relating to the definition and assessment of MSC risks and outlines the gaps that need be addressed in the current research.

2.1 Maritime supply chain risks

MSCs have been suffering from various types of risks, and research has therefore been conducted from different perspectives of risk management in the logistics and transportation domains. Some previous studies focuse on the analysis of relationships between different actors and between safety and costs within a supply chain taking into consideration the impact of some specific risk sources in order to provide a reference for rational decision-making. For example, Wang et al. (2018) investigated optimal insurance premiums for two different contracts (i.e. multiplicative contract and additive contract) between express logistics providers and customs under transportation disruption risk so as to provide insights into the selection of different shipment insurance contracts. Yang et al. (2018) developed a game model based on Bayesian network to determine the optimal inspection strategy of a port authority considering the influence of inspection risk in port state control. Vidyarthi et al. (2007) investigated the trade-off between logistics costs and inventory safety using a nonlinear mixed-integer programming method.

Other research pays more attention to the identification and assessment of risk factors which have negative impact on the safety and efficiency of logistics operations. In this research, risks are generally represented as $Risk = (P, C)$, where P is the occurrence probability of a risk and C is the severity of the consequence. For example, 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. Kumar et al. (2010) defined supply chain risk as the potential deviations from the initial objective, which would result in a decrease of value at different levels. This was also evidenced by a review of 224 journal papers (Ho et al., 2015), which revealed that most of the previous research on supply chain risk assessments paid special attention to the occurrence probability/likelihood of an event, while a few studies assessed the severity of the consequences as well. The combination of P and C presents a simple and effective way to represent a risk. However, a risk is a complex and interdisciplinary concept with a variety of parameters involved in addition to the probability and consequence, such as uncertainty, exposure, and scenarios (Aven, 2012). 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 $Risk = (P, C, U, K)$. Such studies often argue that having two basic risk parameters (i.e. P and C) will lead to the loss of useful information in risk analysis. However, considering more risk parameters is not necessarily better and sometimes not practically feasible. 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, dramatically increasing risk management costs.

In the supply chain domain, a new risk parameter that has attracted attention is visibility. Good visibility in a supply chain will benefit operational efficiency, productivity, and effective planning (Petersen et al., 2005; Yu and Goh, 2014), as well as enhance supply chain stability by mitigating the bullwhip effect (Ouyang, 2007). Furthermore, case studies conducted by Harland et al. (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 became more worrisome given the increasing use of "virtual" supply chains. Internet of things (IoT) technologies 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 the reduction of supply chain uncertainty, thus facilitating more stringent control of product inventory.

2.2 Risk assessment methods

For the assessment of maritime transportation risks, various methods have being developed and applied. Those widely employed risk assessment techniques, yet having close relevance to this work, are introduced in the following subsections.

2.2.1 FMEA

As an inductive and proactive analytical method, FMEA studies the effects of single component failures on the system. Through the control of high-risk failure modes, the overall safety of the system can be increased. It is useful for an exhaustive listing of all potential initiating faults. Three fundamental attributes that have been employed in the traditional FMEA method to calculate the risk priority numbers (RPNs) of each failure are occurrence likelihood, consequence severity, and the probability of failures being undetected. Due to its transparency and easiness, the FMEA method has been widely applied in maritime domains for safety and reliability analyses including Berle et al. (2011), Yang and Wang (2015), and Gul et al. (2017), to name just a few. However, FMEA shows certain incapability when addressing uncertainties, and this, in turn, stimulates the development of some new methods through incorporating uncertainty treatment theories such as fuzzy logic (Liu et al., 2013a), and Bayesian Networks (BNs) (Yang et al., 2008).

2.2.2 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 et al., 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. This kind of system represents human empirical and heuristic knowledge using an approximate and linguistic description that mirrors our own language of communication: IF-THEN rules (Ross, 2009). This makes fuzzy rule-based systems an invaluable tool for expressions when applied in engineering systems with other mathematical models and data processing approaches for reliability analysis and safety assessments (e.g. Kong et al., 2012; Liu et al., 2013b; Polat et al., 2015; Zhang et al., 2016; Wu et al., 2017). Advantages of a fuzzy rule-based system include its ability to capture and preserve irreplaceable human experience, to develop a system that is more consistent than human experts, and to develop solutions faster than human experts can (Abraham, 2005).

2.2.3 Belief rule base

In order to model complex environments and handle uncertain information in the safety management of supply chains, Yang et al. (2006) further extended the classical fuzzy rule-based systems by incorporating the concept of degrees of belief (DoB) into the consequent parts of traditional IF-THEN rules. Belief rule expressions in a fuzzy rule-based system can provide a better compact framework to represent expert knowledge. This enables the system to address a situation where there are DoBs or credibility regarding a hypothesis, but there is insufficient available evidence, or experts are not 100% certain of their judgements (Yang et al., 2007). Based on that, the simple rule can be extended to a so-called belief rule, with all possible consequents associated with belief degrees. A belief rule base (BRB) is a collection of such belief rules. Despite showing advantages over traditional rule-based systems, there are still some potential challenges such as inconsistency, incompleteness during the applications of BRB systems that should not be ignored (Yang et al., 2018), and combinatorial explosion (Wang et al., 2014). The problem of the combinatorial explosion is reflected by an exponential growth of the scale of BRB with the increase of the number of the attributes and the referenced values for each attribute, which will affect its applications in practice. A lot of effort has been put to seek for ways of downsizing the BRB system in order to address this problem. They include the use of the weights of the involved attributes in the IF part to rationalize the distribution of the degree of belief in the THEN part in this paper (e.g. Alyami et al., 2014). It can effectively increase the robustness of the development of fuzzy rules and hence, the accuracy of the risk results.

2.2.4 Bayesian network

The BN (also known as belief networks) method was developed based on the well-defined Bayesian probability theory and networking techniques. 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. 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. For example, Baksh et al. (2018) developed a risk model based on the BN to investigate the possibility of marine accidents considering different operational and environmental factors that affect shipping operations in Arctic waters.

2.3 Research gaps

Although showing some good insights, the aforementioned approaches when being applied to maritime risk analysis, still reveal some specific research gaps as follows:

1) Previous studies on maritime 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.

2) The currently used risk assessment methods revealed incapability and drawbacks in their practical applications, especially when the quantitative analysis of maritime transport risks needs to be conducted in a highly uncertain environment. For example, one of the critically debated limitations of applying the FMEA is that equal RPN values may generate different risk implications (Mandal and Maiti, 2014). Also, the relative importance among the three risk parameters of FMEA is ignored when calculating the RPNs. Furthermore, one common criticism exists in the Bayesian approach is that it requires too much information for the construction of conditional probability tables (CPTs), and this information is often difficult or impossible to obtain in risk assessment. In order to make better use of inference mechanism of BRB systems, different approaches are introduced and incorporated into the BRB system, among which one of the widespread applications is the Rule-base Inference Methodology using Evidential Reasoning (RIMER) (Yang et al., 2006). However, one possible disadvantage of the RIMER approach that hinders its development in practice is its complex calculation process, which is arguably not friendly to mathematically unsophisticated users.

In order to fill the research gaps, this work proposes a novel hybrid fuzzy Bayesian risk analysis method to further address the above theoretical issues in the risk analysis in MSCs. This is achieved by 1) involving an important risk parameter (visibility) of supply chain systems during the construction of fuzzy rule base, and 2) incorporating the BN technique into fuzzy rule-based 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 risk factors. The proposed risk assessment method can process different types of information (e.g. quantitative and qualitative, subjective and objective) from multiple sources in a consistent manner, deal with the uncertainties in risk inputs, and provide accurate results while maintaining a certain degree of visibility, transparency, as well as easiness to operate.

3 Methodology

Normally, the choice of the approaches in risk studies depends on several elements including the data availability (qualitative and qualitative information), the degree of interrelationships complexity, and the causes of uncertainty. A common problem in risk assessment in the shipping industry is the lack of objective failure data. Thus, subjective and qualitative information is usually involved as a complementary input for the risk assessment, which will inevitably bring uncertainties due to the vagueness or imprecision of human judgements. Another contributor to the uncertainty in MSC risk assessment is the complexity of the maritime logistics system where different risk parameters may need to be considered in order to fulfil the requirements under different risk situations. In view of this, a fuzzy belief rule-based Bayesian network (FBRB-BN) approach is proposed to assess the MSC risks under uncertainties, in which fuzzy logic is used to deal with data vagueness and Bayesian inference is to facilitate the rule synthesise. The major advantage of this method is the ability to model the relationships between risk attributes/parameters and risk status in a flexible manner (e.g. fuzzy risk input and output will be not necessarily presented in a linear relation) and to process multi-source information and transform it into subjective conditional probabilities in the BN, in order to effectively tackle uncertainties for precise risk assessment in the maritime industry.

The proposed method consists of five major components. The relationships of these steps and how these research steps help address research questions and achieve the research objectives are depicted in Figure 1. Details on how to conduct these research steps are stated in the following subsections.

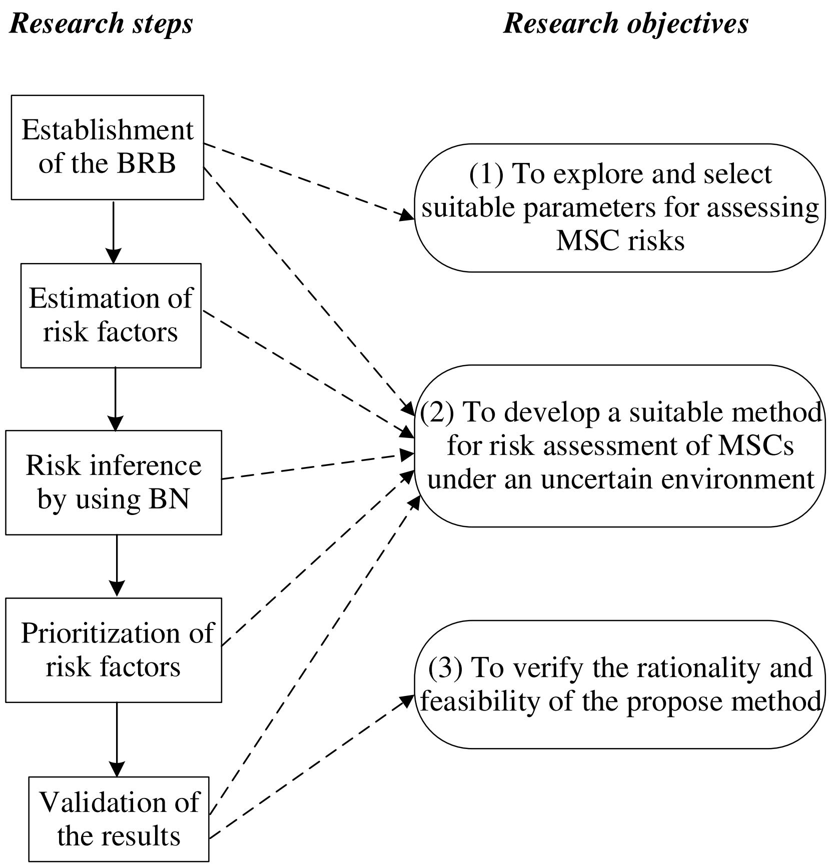

Figure 1. The major research steps and their relations with the research objectives

3.1 Establishment of the BRB for risk assessment of MSCs

In this paper, two main extensions of risk parameters are considered during the construction of the BRB for MSC risk assessment. One is the *visibility* of risk in an MSC (Vilko et al., 2016), and the other is the decomposition of *consequence* into three categories based on different types of impacts on the maritime transportation. From the perspective of theoretical risk contributions, this horizontal addition and vertical specification of risk parameters in two tiers lead to new ways of constructing a fuzzy rule base in risk analysis.

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. In recent research of risk analysis in container shipping operations, Chang et al. (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. According to the features of the maritime shipping industry, the study subdivides the risk consequence into three categories, which are *time delay/disruption*, *additional cost*, and *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 types of 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 an MSC, where the minimum requirements cannot be achieved. The parameter *time delay/disruption* has been widely studied in the context of container shipping (e.g. Ghadge et al., 2013; Chang et al., 2014; Vilko et al., 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 Oketch, 2011). *Damage to quality* refers to the damage to any component within an MSC, including transported goods, port infrastructure, and vessels.

Obviously, the above-discussed risk parameters are not bound in a linear relationship, and to a large extent, their evaluations cannot be effectively supported by objective data. Hence, a fuzzy belief rule-based approach is employed here. Based on the above-mentioned risk parameters, the BRB can be constructed according to Eq. (1) (Yang et al., 2006).

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

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 complete; otherwise, it is incomplete.

In the constructed BRB system, five risk parameters are considered as the antecedent attributes in fuzzy rules (the IF part). They are risk occurrence likelihood (L), visibility (V), consequence severity in terms of time delay/disruption (CT), additional cost (CC), and damage to quality (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 associated with the five antecedent attributes and conclusion, a set of linguistic variables are defined. The linguistic variables for describing each attribute are decided based on the situation in the case of interest, with reference to the relevant studies in the literature. It is suggested that the linguistic variables used to describe risk parameters L, V, CT, CC, and CQ in the shipping industry can be defined as follows. To estimate L (Alyami et al., 2014), 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 (Alyami et al., 2014) are often “good”, “normal”, and “poor.” Variables (CTk, k =1, 2, 3) used to estimate CT (Vilko et al., 2016) are often “low”, “medium”, and “high.” Variables (CCl, l =1, 2, 3) used to estimate CC (Vilko et al., 2016) are often “low”, “medium”, and “high.” Variables (CQm, m =1, 2, 3) used to estimate CQ (Vilko et al. 2016) 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”. Although only three variables for each risk parameters are considered in this paper for a better practicality purpose, it is possible to have some flexibility in the number and definition of variables to suit different risk scenarios, and examples can be found in the research by Yang et al. (2008). However, the changes of the defined variables and their numbers require a very careful justification from domain experts.

With respect to the conclusion of a BRB, the DoB of the rules can be assigned based on knowledge accumulated from past events (Alyami et al., 2014) or directly using knowledge from multiple experts (Yang et al., 2009). However, in practice, it is difficult to determine all the DoBs of rules rationally in a BRB by only using experts’ subjective knowledge, especially for a large-scale BRB with hundreds or thousands of rules (Yang et al., 2017). Given this, a proportion method was proposed by Alymai et al. (2014) to rationalise the distribution of DoB. The method provided a logical and straightforward way to calculate the DoB in the THEN part. However, one major deficiency is the ignorance of the weight of risk parameters when calculating the DoB. This may affect the robustness of the BRB when the importance of the attributes is significantly different. Thus, the relative importance of the antecedent attributes should be appropriately considered when developing a rule representation in this study.

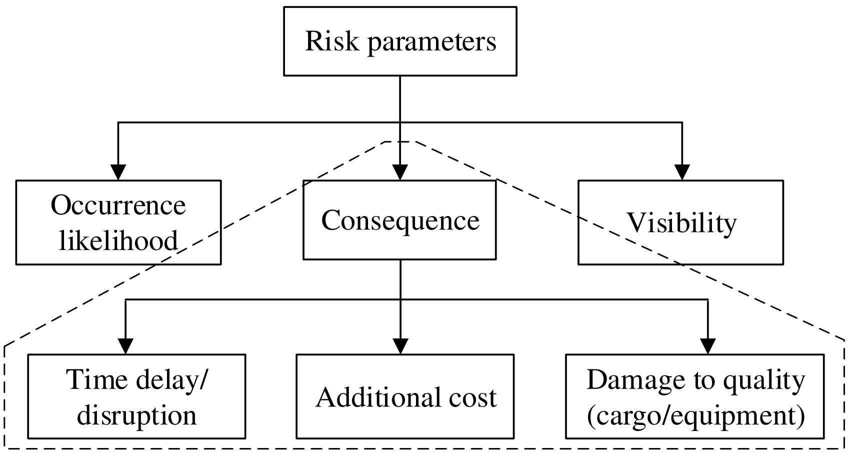

Figure 2. The hierarchical structure of the five risk parameters

The relationship of the risk parameters can be seen in Figure 2. It is a two-level hierarchical structure, where the first level consists of the three basic risk parameters, while the second one is composed of the sub-parameters of consequence. In light of this structure, the weight of each risk parameter can be calculated using an AHP method based on the evaluations of three domain experts (refer to Section 4 for their detailed information). The consistency of the results was checked, and the low inconsistency ratios (< 0.1) of all pairwise comparisons verified the rationality of the results. They are shown in Table 1.

Table 1 Weight of each risk parameter in the BRB

<table>
<tr><th colspan="2">Risk parameters (antecedent attribute)</th><th colspan="2">Local weight</th><th>Global weight</th></tr>
<tr><td colspan="2">Occurrence likelihood (L)</td><td colspan="2">0.18</td><td>0.18</td></tr>
<tr><td colspan="2">Visibility (V)</td><td colspan="2">0.08</td><td>0.08</td></tr>
<tr><td rowspan="3">Consequence severity</td><td>Time delay (CT)</td><td rowspan="3">0.74</td><td>0.47</td><td>0.35</td></tr>
<tr><td>Additional cost (CC)</td><td>0.11</td><td>0.08</td></tr>
<tr><td>Quality damage (CQ)</td><td>0.42</td><td>0.31</td></tr>
</table>

The relative importance of each risk parameter is considered when approaching the DoB distribution, using the proportion method. All attributes in both IF part and THEN part are described by variables with three grades; as such, for any specific conclusion attribute, the DoB belonging to a specific grade can be calculated by summing the normalised weights of all risk parameters with the "same" grade. *Rule* 2 provides 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 with Low (or equivalent) and Medium (or equivalent) grades are 0.69 (0.18+0.08+0.35+0.08) and 0.31 (CQ, 0.31), respectively. Therefore, the DoBs belonging to Low and Medium in the *R* are 69% and 31%, respectively[1]. Similarly, the BRB used in risk assessment of MSCs containing 243 (3^5) rules can be developed, partially shown in Table 2 (such a rule base represents functional mappings between antecedents and conclusions).

Table 2 The BRB in the risk assessment of MSCs

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
…	…	…	…	…	…	…	…	…
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

[1] If the number of the linguistics variables of the five attributes and conclusion are different, the fuzzy link based approach (Yang et al., 2009) can be applied in this process to calculate the DoB in the conclusion.

…	…	…	…	…	…	…	…	…
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

3.2 Data collection and estimation of risk factors

Risk parameters in the antecedents are estimated with respect to each identified risk factor using available data. The estimated results are transformed into a unified form so that they can be appropriately used in a BRB system for risk inference. In a traditional BRB system, membership functions are generally used to model linguistic variables. Some typical inputs (e.g. a single deterministic value, an interval, a triangular distribution, and a trapezoidal distribution) may be encountered due to the possible uncertainties involved (Eleye-Datubo, 2004). They are usually represented using fuzzy membership functions based on historical data or expert experience (Yang et al., 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 have debated the merits of such observation transformation operations, because the risk analysis results are sensitive to the qualitative judgment of the linguistic variables used (e.g. Braglia et al., 2003; Yang et al., 2008). Thus, this study employed a subjective probability method to address this concern. Subjective probability is a probability derived from an expert's judgment about the degrees of a specific linguistic variable to which one risk parameter belongs. In the subjective probability method, risk parameters are estimated and represented using the probability distribution of the linguistic variables, provided directly by experts.

A questionnaire survey was designed to collect experts' judgements about risk parameters in terms of the investigated MSC risk factors. By using the questionnaire as designed in Appendix A, experienced staff members who have closely worked to ensure the safe and efficient operations of the investigated MSC were selected for the case study. The subjective probability distributions from multiple expert judgments are merged using a weighted average approach (Wan et al., 2015) based on the relative importance of each expert.

3.3 Risk inference using a BN technique

Once all the required data have been collected and prepared, a BN technique is applied to conduct risk inference. The reason for selecting BN in this research is that it has been proved to be a better approach (Yang et al., 2008) being capable of delivering accurate result in a fast and reliable manner, as it overcomes the drawbacks of traditional rule synthesise methods, including the information loss of the fuzzy Min-Max operation and computing complication of the evidential reasoning approach. Moreover, its ability to capture non-linear causal relationships makes it an appropriate tool to synthesise the DoBs of different rules (Alymai et al., 2014). To achieve rule aggregation, the BRB developed in Section 3.1 is first represented in the form of conditional probabilities. For example, Rule #2 in Table 3 is displayed using Eq. (1) as follows (Yang et al., 2017):

R_2: IF *Unlikely (L*1*)*, *Good (V*1*)*, *Low (CT*1*)*, *Low (CC*1*)*, and *Moderat*e (*CQ*2), THEN {(*Low* (*R*1), 0.69), (*Medium* (*R*2), 0.31), (*High* (*R*3), 0)}.

This expression can be represented in the form of conditional probability as follows.

Given *L*1, and *V*1, and *CT*1, and *CC*1, and *CQ*2, the probability of

Rh (*h* = 1, 2, 3) is (0.69, 0.31, 0), or

$$p\,(Rh \mid L1, V1, CT1, CC1, CQ2) = (0.69, 0.31, 0) \qquad \text{Eq. (2)}$$

where "|" symbolizes conditional probability.

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

Subjective probabilities obtained from observations during the questionnaire survey are considered to be prior probabilities of every parent nodes. In this way, the prior probabilities of nodes N_L, N_V, N_{CT}, N_{CC}, and N_{CQ}, can be computed as $p\,(Li) = \beta_i$, $p\,(Vj) = \beta_j$, $p\,(CTk) = \beta_k$, $p\,(CCl) = \beta_l$, and $p\,(CQm) = \beta_m$, respectively. Then, Eq. (3) is used to calculate the marginal probability of N_R (Jensen and Nielsen, 2007).

$$p(Rh) = \sum_{i=1}^{3}\sum_{j=1}^{3}\sum_{k=1}^{3}\sum_{l=1}^{3}\sum_{m=1}^{3} p(Rh \mid Li, Vj, CTk, CCl, CQm)\,p(Li)\,p(Vj)\,p(CTk)\,p(CCl)\,p(CQm) \qquad \text{Eq. (3)}$$
$$(h = 1, 2, 3)$$

3.4 Prioritisation of risk factors with utility functions

Appropriate utility values U_{Rh} are required to transform DoBs of risk status of each risk factor into crisp values for ranking purposes. The utility values can be defined by combining some specific fuzzy rules (Wang et al., 1995) and risk scores, satisfying the following conditions.

1) IF *Unlikely (L*1*)*, *Good (V*1*)*, *Low (CT*1*)*, *Low (CC*1*)*, and *Negligible* (*CQ*1),

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

2) IF *Occasional (L*2*)*, *Normal (V*2*)*, *Medium (CT*2*)*, *Medium (CC*2*)*, and *Moderate* (*CQ*2),

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

3) IF *Frequent (L*3*)*, *Poor (V*3*)*, *High (CT*3*)*, *High (CC*3*)*, and *Critical* (*CQ*3),

THEN {(*Low* ($R1$), 0), (*Medium* ($R2$), 0), (*High* ($R3$), 1)}.

The risk score (*RS*) describes the individual grade of each linguistic 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 the final risk status), and 3 means the "highest level" (contributing the most to the final risk status). Consequently, the values of U_{Rh} can be calculated as (Yang et al., 2014):

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

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

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

Eq. (4) is used to develop a new risk priority index (*RPI*):

$$RPI = \sum_{h=1}^{3} p(Rh)U_{Rh} \qquad \text{Eq. (4)}$$

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

3.5 Validation using sensitive analysis

When a new model is developed, a careful test is required to verify its soundness. This testing is especially important and desirable when subjective elements are involved in the model's evaluation process. In this study, a sensitivity analysis is conducted to test the robustness of the belief structures, and logicality of the FBRB-BN method proposed. Sensitivity analysis provides an analytical judgment for *RPI*. It checks how sensitive the outputs (the risk assessment results or *RPI*) are to the 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 follow these three axioms (Yang et al., 2008; Jones et al., 2014):

Axiom 1. A slight increase/decrease in the prior subjective probabilities of each input node should 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 magnitude of influence on the *RPI* will remain consistent with their weight distributions.

Axiom 3. The total magnitude of the influence of the combined 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 Results and discussion

In previous research (i.e. Wan et al., 2018), 64 risk factors from maritime container supply chains were identified from five major perspectives (which are society, natural environment, management, infrastructure and technology, and operations), and the identified risk factors were further classified into different levels according to their risk values. The top five risk factors in terms of their likelihood and consequence are "fluctuation of fuel price", "fierce competition", "change of exchange rates", "unattractive markets", and "transportation of dangerous goods". In Wan et al. (2018), a basic risk analysis method, risk matrix, was used and the results indicated that some risk factors received very close risk scores, requiring an advanced method to be developed to distinguish their true difference in terms of risk implications. This case study, aiming to address this research gap from a practical perspective.

This paper considers a world's leading container shipping company to be the test case. By the end of February 2018, the case company 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), among the TOP 5 in the world for the scale of the container fleet. Thus, it is a representative case study of the maritime network analysis considering both its leading role in shipping companies worldwide and the accessibility in terms of data collection. The assessment of the five selected risk factors with respect to the company's one specific and representative MSC was conducted to demonstrate the feasibility of the proposed method in the risk assessment of MSCs[2]. A questionnaire was conducted with three senior staff from different departments of the company who are the decision makers being in charge of the safety of the investigated chain collectively. The qualification of the selected experts is summarized as follows:

- Expert No. 1: Senior Captain, technical safety department; has worked onboard ships on different container shipping routes for more than 12 years.
- Expert No. 2: General Manager, marine operations centre; involved in the safety and security management of global container fleets for more than 12 years.
- Expert No. 3: Marketing Manager, liner trade management group; has worked in the container shipping company for more than 15 years.

Due to the similar seniority of the three experts, equal weight was assigned to each expert when combining their evaluations. The data collected from them were applied in the FBRB-BN method for analysing and ranking the MSC risks.

4.1 Ranking of the investigated risk factors

Taking the assessment of risk factor "fluctuation of fuel price" as an illustration, Table 3 shows the estimations from three experts in terms of the five risk parameters.

[2] The investigated MSC involving international shipping and ports from difference continents, has the characteristics of generalisation representing MSCs. The top five risk factors evaluated in Wan et al., (2018) are revisited in this case.

Table 3 Expert evaluation results for "fluctuation of fuel price."

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

Similarly, estimations of all risk factors in terms of each risk parameter can be obtained, and then they are transformed into the format of prior probability by using Eq. (2) for realising risk inference.

According to Eq. (3), the risk status of "fluctuation of fuel price" can be calculated as $p(Rh)$ = (51.7%, 32.3%, 16.0%). A total of 162 out of 234 rules in the established BRB are hired during the calculation process. The result is expressed as {(Low, 51.7%), (Medium, 32.3%), (High, 16.0%)}; in other words, the risk status associated with the "fluctuation of fuel price" is low with a 51.7% DoB, medium with a 32.3% DoB, and high with a 16.0% DoB. The calculation was modelled using *GeNle 2.0* software to facilitate BN computation. Figure 2 provides an example.

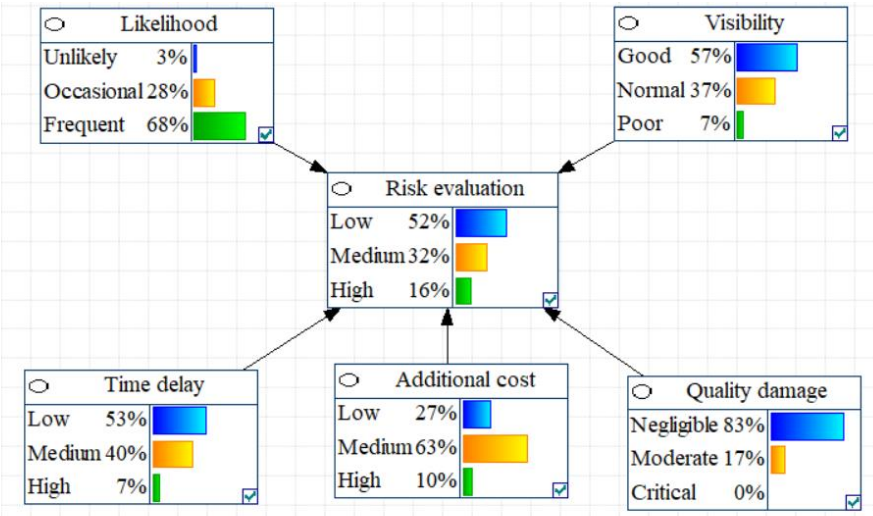

Figure 3 Risk assessment of "fluctuation of fuel price" (using *GeNle 2.0* software)

As shown in Figure 3, any risk input modification related to the five risk parameters can trigger a change of the output node. This helps automate the instant risk assessment of any target risk factors within an MSC. In a similar way, the risk status of other selected risk factors can be obtained as follows:

The risk status of "fierce competition"

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

The risk status of "change of exchange rates"

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

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%)}.

The risk status of risk factors expressed by linguistic variables with DoBs requires further analysis for their risk prioritisation. The *RPI* of risk factor "fluctuation of fuel price" is calculated using Eq. (4) with the utility values described in Section 3.4:

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

In a similar way, the *RPI* values of "fierce competition," "change of exchange rates," "unattractive markets," and "transportation of dangerous goods" are calculated to be 47.62, 45.04, 46.50, and 52.19, respectively. Therefore, the shipping line's transportation of dangerous goods requires more attention with respect to supply chain risk management compared to other risk factors. Table 4 lists the *RPI* values of all risk factors and their rankings.

Table 4 *RPI* values of some major risk factors

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

4.2 Comparative analysis of different risk assessment methods

To further illustrate the practicality and advantages of the proposed method, the results obtained from the FBRB-BN method are compared with that from other representative risk assessment methods (e.g. risk matrix, risk scale analysis and FMEA) used in maritime domains when investigating the same case, as summarised in Table 5.

Table 5 Results obtained from other MSC risk assessment methods

Risk factors	**RM***	**Rank**	**RSA****	**Rank**	**FMEA*****	**Rank**
	Risk level		*Risk scale*		*RPN*	
Fluctuation of fuel price	High	1	10.68	2	144	2
Fierce competition	Moderate	2	9.77	4	120	3
Change of exchange rates	Moderate	2	8.53	5	105	4
Unattractive markets	Moderate	2	9.99	3	120	3
Transportation of dangerous goods	High	1	11.01	1	189	1

* RM=Risk matrix, usually calculated by the sum of likelihood and severity. See Yang (2010) for details.
** RSA=Risk scale analysis, usually calculated by the product of likelihood and severity, with values ranging from 1 to 25, and see Chang et al. (2014) for details.
*** Usually calculated by the occurrence likelihood, consequence severity and probability of failures being undetected, with values ranging from 1 to 1000. See Ioannis et al. (2013) for reference.

It can be seen that the results obtained by the risk matrix method are usually qualitative, which is more suitable for the preliminary screening of the identified risk factors rather than ranking given there are too many factors sharing the same risk scores. Like most of the risk assessment methods, the risk scale analysis only considers two risk parameters, which may not be able to provide a comprehensive reference for decision making in specific industrial cases. Besides, the results from risk scale analysis showed a low degree of discrimination. Regarding the traditional FMEA, one shortfall is that the same RPNs produced by different risk factors may hinder the prioritization and provide misleading information to decision-makers. More importantly, these traditional risk assessment methods showed the inherent drawbacks of addressing uncertainties. The rankings according to different risk assessment methods are compared and depicted in Figure 4.

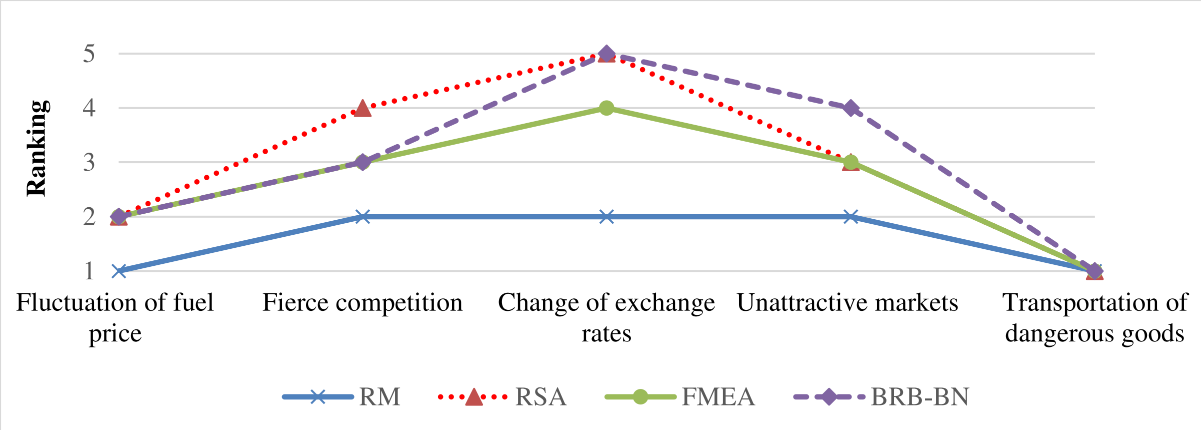

Figure 4 Ranking of risk factors with respect to different methods

Except for the risk matrix (which cannot provide enough information for full ranking), the ranking results obtained by other methods are consistent to a great extent, validating the feasibility of the proposed methods. By comparing this result with the ranking of the risk factors from Wan et al. (2018), it can be found that in terms of the ranking of economic-related risk factors (i.e., fierce competition, fluctuation of fuel price, change of exchange rates, and unattractive markets), results from both studies show a similar ranking trend. However, the fluctuation of fuel price shows a relatively higher influence on an individual shipping company compared with that of the whole shipping industry. Another major difference is the ranking of operational-related risk factors. In the study by Wan et al. (2018), "transportation of dangerous goods" ranked the fifth, showing lower impacts compared with economic-related risk factors. In this study, however, this risk factor ranks the first due to its poor visibility, high additional cost, and severe damage to both cargo and ships when an accident occurs. According to the investigated company, the poor visibility of this risk factor is mainly due to the fact that some shippers tend to hide cargo information because shipping companies often charge expensive freight fees and insurance to transport expensive cargo and dangerous goods. Furthermore, our research "refines" the findings of some previous studies by providing quantitative risk prioritisation information. For example, in line with the research findings of Notteboom and Vernimmen (2009), and Chang et al. (2014), this research discloses that the fluctuation of fuel price is an important risk factor in the shipping operations. It ranks the second with both high likelihood and consequence, which deserves the attention of shipping companies. Our research findings also emphases that the transportation of dangerous goods is an important risk factor, which was ranked the first among all operational risks of the container shipping industry in terms of safety and security incident-related loss by Chang et al. (2015).

4.3 Validation of the model

A sensitivity analysis is conducted to test the robustness of the proposed FBRB-BN model and the logicality of the established BRB according to the three axioms introduced in Section 3.5. First, the relationship between the risk status (or *RPI*) of risk factors and the five risk parameters attributes (i.e. the *L, V, CT, CC* and *CQ*) requires clarification. The linguistic variables of all risk parameters are positively correlated with the *RPI* values; as such, the relationship can be easily identified and described. The *RPI* value is higher when the linguistic variable of each risk parameter is worse (here, "worse" is defined, for example, as a higher likelihood, time delay, additional cost, quality damage, and poorer visibility).

Next, a subjective probability of 10% is reassigned to different linguistic variables of each risk parameter and moved toward the maximum increment of *RPI*. If the model reflects logical reasoning, the *RPI* should increase accordingly. For example, if the subjective probability that the risk factor "transportation of dangerous goods" belongs to "frequent" increases by 0.1, and correspondingly, the one belonging to "unlikely" decrease by 0.1, then the *RPI* of the 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 one belonging to "good" decreases by 0.1, then the *RPI* of this risk factor increases from 52.16 to 54.09.

Similar studies were conducted to investigate the variation between any two linguistic variables relating to the five risk parameters. All the results are consistent with **Axiom 1** in Section 3.5. Regarding the same axiom, we tested and validated the consistency of the BRB 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 abruptly change with respect to variation between two neighbouring linguistic variables of each risk parameter. For example, assume a set of rules in which all *L* belongs to "unlikely," *V* belongs to "good," *CT* belongs to "low," and *CQ* belongs to "negligible" (i.e. locked evidence in BN); 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" delivered changes of the *RPI* values from 1 to 3.48, and then to 20.36. Similarly, the values of all rules in the BRB were checked using *GeNle 2.0* software, demonstrating the consistency and logicality of the BRB.

The sensitivity study reveals that *RPI* values are sensitive to risk parameters. However, the study was based on point changes, rather than gradual variations in intervals (i.e. [0, 0.1]). As such, the analysis does not effectively disclose the impact magnitude of the subjective probability changes on the *RPI* values. To study the impact magnitude, a sensitivity analysis based on an interval [0, 0.1], where the change of the subjective probability from 0 to 0.1 with a step of 0.02, was used for each risk parameter toward the maximal increment of the *RPI*. Figure 5 shows that the impact magnitudes of the subjective probability changes on the *RPI* are significantly different. Such magnitudes closely follow the weight ratio among the five attributes - *L, V, CT, CC* and *CQ* - when developing the BRB, being 0.18:0.08:0.35:0.08:0.31, respectively (as shown in Table 2). This is consistent with **Axiom 2** introduced in Section 3.5, indicating the robustness of the developed BRB in this work.

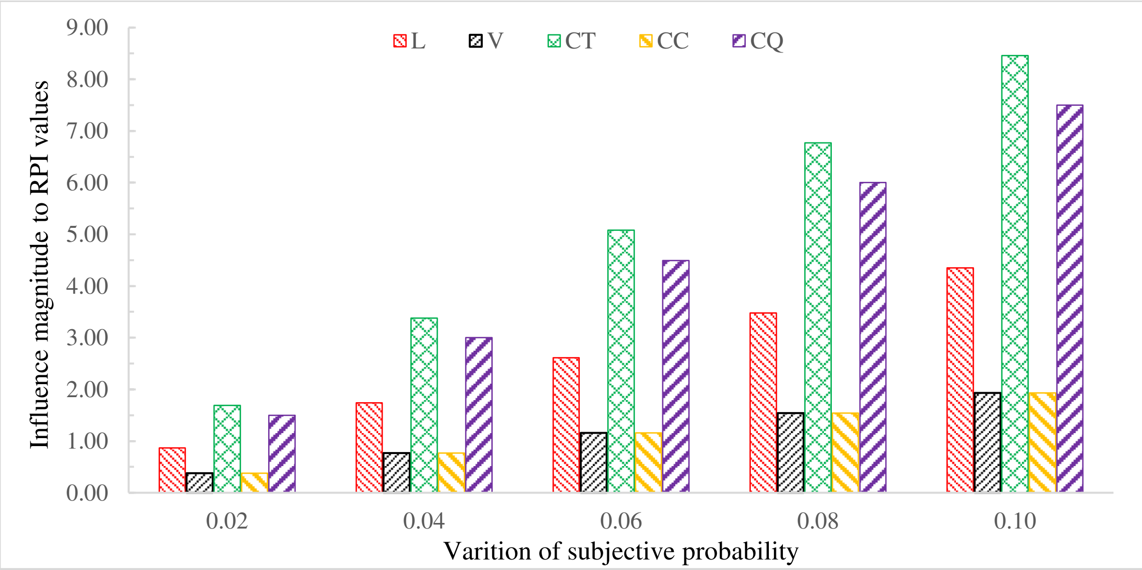

Figure 5 Sensitivity analysis of influence magnitudes from different attributes

The previous discussion mainly focuses on subjective probabilities. In the next step, an analysis was conducted to assess the effect of risk parameter variation on *RPI* values. The variation considered the different combinations of the risk parameters. To study the magnitude of their influence on *RPI* values, 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 were considered. The five groups are classified according to the number of risk parameters to be tested. For instance, the first group takes into account the change of variables of a single parameter, the second group involves the change of variables of any two combined parameters, and so on. The five groups are shown in Table 7 with different colours (from combination #2 to #32). According to **Axiom 3**, if the model reflects the reality, then the magnitude of the five groups' influence on the values will consistently vary in an ascending/descending order among these groups. This can be assessed by comparing the individual effects of the variations with their corresponding *RPI* values. For illustration purposes, the assessment results associated with risk factor "transportation of dangerous goods" is used as an example. A 10% subjective probability is reassigned to different variables associated with each risk parameter, towards a maximum increment of *RPI* values. Table 6 shows the *RPI* values in terms of the influence from each combination of the risk parameters, along with the variations.

Table 6 Sensitivity analysis of the magnitude of influence 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 maximum increment of *RPI*.

Combination #1 shows a baseline of the *RPI*; it shows the original assessment result of the risk factor "transportation of dangerous goods." The 31 combinations are listed from #2 to #32; they are grouped into five different groups in different colours. Using Combination #27 as an example (evidence), the effect of this combination on *RPI* values can be calculated as 16.69 (=68.85-52.16). The influence magnitude of its sub-evidence on *RPI* values can then be calculated; they are 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 on *RPI* values shows that 16.69 is the largest among all selected combinations.

Therefore, the model is validated in this example. The additional investigation was conducted using other combinations and risk factors. The results are consistent with **Axiom 3,** supporting the soundness and logic of the model.

5 Summary of contributions

This research aims to fulfil the research gaps in risk assessment of MSC research regarding the quantitative assessment and prioritisation of risk factors under uncertainties. In this study, more risk attributes/parameters are investigated according to the features of the maritime container shipping industry in order to measure those risk factors in a precise manner. The contributions of this work can be concluded from both theoretical and practical perspectives as follows.

As far as the theoretical contributions are concerned, combining fuzzy rule bases with a belief structure and BNs provides a powerful tool to incorporate subjective judgments to evaluate risks and prioritise risk factors under uncertainty especially when risk records are incomplete. In the proposed research method, subjective risk analysis using probability assigned against the pre-defined linguistic variable has been proposed to address high uncertainty in data. Presenting risk inputs as a probability distribution on linguistic variables enables different types of uncertain information to be modelled using a unified form, providing a possibility for multi-source information fusion through the proposed method. Compared to other fuzzy approaches such as Min-Max operation, this method overcomes the weakness of the loss of useful information in fuzzy risk inference. As the fuzzy logic is only used in the establishment of the BRB, the estimation of risk factors will be minimally affected by the subjective/fuzzy judgment of linguistic variables used in antecedence. Furthermore, the usage of BN facilitates the risk inference, and it is able to update the risk reference results in a timely manner when new inputs are incorporated.

The results of this study also contribute to managerial practices in the realms of MSC. Firstly, it shows all the outstanding risk factors through a wide range of survey. Secondly, this study highlights the importance of visibility in the risk assessment of MSCs. As the visibility may significantly vary across different actors of an MSC, extensive co-operation and information sharing among the actors of an MSC will be helpful for better system-level risk management (Vilko et al., 2016). Thirdly, the decomposition of risk consequences into different categories according to the nature of their impacts is able to provide richer information for managers with respect to different decision-making requirements and helps them allocate limited resources to the most impactful risks. Finally, the research provides a possibility of comparing and integrating the risk factors of different perspectives in one single framework, and the proposed method can be either used as a stand-alone technique to prioritise risk factors with *RPI* values or can be integrated into the risk-based decision-making method to evaluate the effectiveness of different risk control options in the future.

It is also noteworthy that the proposed method provides a standard, generic framework for the assessment of risk factors of MSCs. Although it is applied and demonstrated in a case study of the container shipping industry, it has the potential and flexibility to be tailored for wider applications in different supply chain industries. However, it is noteworthy that the developed BRB in this study needs to be reconstructed accordingly to best fit the investigated scenarios. 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, will need to be selected according to the features of other industries and specific requirements of carrying out the risk assessment.

6 Conclusion

Under a competitive global market, the increasing complexity of MSC systems and various types of uncertainties in maritime risks have highlighted the necessity of creating a flexible and effective method for assessing MSC risks. In this study, we propose a novel FBRB-BN method for MSC risk management, where the BRB models the relationships between risk parameters and risk status in a logical way; the BN technique is used to conduct risk inference. A new weighted utility function is applied to transform the DoBs of risk status into numerical values to rank risk factors. The case study of a world-leading container shipping company reveals that the risk factor “transportation of dangerous goods” is the most significant one in terms of the investigated MSC, followed by the “fluctuation of fuel price”, “fierce competition”, “unattractive markets”, and “change of exchange rates”. Compared to the traditional risk analysis methods, the new method provides sensitive and flexible risk results in real situations, without sacrificing easiness of the modelling process and transparency of information passing through the model for the final result.

To overcome the limitations of the current study, collecting more responses from other international MSC companies allocated in different regions will be helpful to improve the generalization of the results although the selected case (i.e. a world-leading container shipping line) is representative. Additionally, in future research, the proposed method can be applied to and adapted to other industries to test its feasibility in a wider context. It is suggested that more attention should be paid to the risk assessment of a supply chain system from a systemic perspective considering the relationships among different components and the relevant impacts of their risk status on the safety performance of the whole system.

Acknowledgement

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Appendix A

Questionnaire survey

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, additional cost, and damage to quality. Explanations of linguistic grades of each risk parameter are shown in Table 7.

Table 7. 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 fewer 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
Damage to quality	*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 8):

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 9.

Table 8. 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. Damage to Quality (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 9. 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. Damage to Quality		
	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 B

Table 10 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

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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

***L**= Likelihood (L1=unlikely, L2=occasional, and L3=frequent); **V**= Visibility (V1=good, V2=normal, and V3=poor); **CT**= Consequence severity in terms of time delay (CT1= low, CT2=medium, and CT3=high); **CC**= Consequence severity in terms of additional cost (CC1= low, CC2=medium, and CC3=high); **CQ**= Consequence severity in terms of quality damage (CQ1= negligible, CQ2=moderate, and CQ3=critical); **R**= Risk status (R1=low, R2=medium, and R3=high).*

Reference

Abraham A. (2005). *Rule-based expert systems*. In: Handbook of measuring system design, edited by Sydenham, P. H. and Thorn, R. New York: John Wiley & Sons Ltd.

Alyami, H., Lee, P. T. W., Yang, Z., Riahi, R., Bonsall, S., & Wang, J. (2014). An advanced risk analysis approach for container port safety evaluation. *Maritime Policy & Management*, *41*(7), pp. 634-650.

Anthony Cox, L. (2008). What's wrong with risk matrices? *Risk Analysis, 28*(2), pp. 497-512.

Asgari, N., Hassani, A., Jones, D., & Nguye, H. H. (2015). Sustainability ranking of the UK major ports: methodology and case study. *Transportation Research Part E: Logistics and Transportation Review*, 78, 19-39.

Aven, T. (2012). The risk concept—historical and recent development trends. *Reliability Engineering & System Safety*, *99*, pp. 33-44.

Baksh, A. A., Abbassi, R., Garaniya, V., & Khan, F. (2018). Marine transportation risk assessment using Bayesian Network: Application to Arctic waters. *Ocean Engineering*, 159, 422-436.

Ben-Gal, I. (2007). *Bayesian networks*. In: Encyclopedia of Statistics in Quality and Reliability, edited by Ruggeri F., Faltin F. and Kenett R. New Jersey: John Wiley and Sons.

Berle, Ø., Rice Jr, J. B., & Asbjørnslett, B. E. (2011). Failure modes in the maritime transportation system: a functional approach to throughput vulnerability. *Maritime Policy & Management*, 38(6), 605-632.

Braglia, M., Frosolini, M., & Montanari, R. (2003). Fuzzy criticality assessment model for failure modes and effects analysis. *International Journal of Quality & Reliability Management*, *20*(4), pp. 503-524.

Chang, C.H., Xu, J. and Song, D.P. (2014). An analysis of safety and security risks in container shipping operations: A case study of Taiwan. *Safety Science*, 63, pp.168-178.

Chang, C.H., Xu, J. and Song, D.P. (2015) Risk analysis for container shipping: from a logistics perspective. *The International Journal of Logistics Management*, 26(1), pp.147-171.

Chen, J., Chen, T., Ying, S., & Shi, C. (2011). Safety management of work vessel in deep water based on fault tree analysis. *International Conference on Information Technology, Computer Engineering and Management Sciences* (Vol.3, pp.377-380). IEEE.

Eleye-Datubo, A. G., Sii, H. S., Wang, J., Yang, J. B., & Liu, J. (2004). The application of approximate reasoning methodologies to offshore engineering design based on risk assessment. In *Proceedings of the 7th Biennial ASME Conference on Engineering System Design and Analysis (ESDA),* Manchester, England, 19th -22nd July 2004.

Gorman, G. (2015). *West Coast ports to begin tackling backlog after labour deal*, Reuters: Los Angeles CA. Available from: http://www.reuters.com/article/ 2015/02/21/us-usa-ports-west-idUSKBN0LO1K620150221.

Gul, M., Celik, E., & Akyuz, E. (2017). A hybrid risk-based approach for maritime applications: The case of ballast tank maintenance. *Human and Ecological Risk Assessment: An International Journal*, 23(6), 1389-1403.

Harland, C., Brenchley, R., & Walker, H. (2003). Risk in supply networks. *Journal of Purchasing and Supply Management*, 9(2), pp. 51-62.

Ho, W., Zheng, T., Yildiz, H. & Talluri, S. (2015). Supply chain risk management: a literature review. *International Journal of Production Research*, 53(16), pp. 5031-5069.

IMO, 2012. *Guide to Maritime Security & ISPS Code*. International Maritime Organization, London.

Ioannis, D., Theodoros, L., & Nikitas, N. (2013). Application of FMEA to an offshore desalination plant under variable environmental conditions. *International Journal of Performability Engineering*, 9(1), 105-116.

Jensen, F. V. and Nielsen, T. D. (2007). *Bayesian networks and decision graphs*, 2rd edition. NY, USA: Springer-Verlag.

Jones, B., Jenkinson I.D., Yang Z. & Wang J. (2010). The use of Bayesian network modelling for maintenance planning in a manufacturing industry. *Reliability Engineering & System Safety*, *95*(3), pp. 267-277.

Kong, G., Xu, D. L., Body, R., Yang, J. B., Mackway-Jones, K., & Carley, S. (2012). A belief rule-based decision support system for clinical risk assessment of cardiac chest pain. *European Journal of Operational Research*, *219*(3), pp. 564-573.

Liu, H. C., Liu, L., & Lin, Q. L. (2013a). Fuzzy failure mode and effects analysis using fuzzy evidential reasoning and belief rule-based methodology. *IEEE Transactions on Reliability*, 62(1), 23-36.

Liu, H. C., Liu, L., Lin, Q. L., & Liu, N. (2013b). Knowledge acquisition and representation using fuzzy evidential reasoning and dynamic adaptive fuzzy Petri nets. *IEEE Transactions on Cybernetics,* 43(3), 1059-1072.

Liu, H. C., Lin, Q. L., & Ren, M. L. (2013c). Fault diagnosis and cause analysis using fuzzy evidential reasoning approach and dynamic adaptive fuzzy Petri nets. *Computers & Industrial Engineering*, 66(4), 899-908.

Liu, J., Yang, J. B., Wang, J., SII, H. S., & Wang, Y. M. (2004). Fuzzy rule-based evidential reasoning approach for safety analysis. *International Journal of General Systems*, *33*(2-3), pp. 183-204.

Manuj, I., & Mentzer, J. T. (2008). Global supply chain risk management. *Journal of business logistics*, *29*(1), pp. 133-155.

Notteboom, T. E., & Vernimmen, B. (2009). The effect of high fuel costs on liner service configuration in container shipping. *Journal of Transport Geography*, 17(5), pp. 325-337.

Ouyang, Y. (2007). The effect of information sharing on supply chain stability and the bullwhip effect. *European Journal of Operational Research*, 182(3), pp. 1107-1121.

Petersen, K. J., Ragatz, G. L., & Monczka, R. M. (2005). An examination of collaborative planning effectiveness and supply chain performance. *Journal of Supply Chain Management*, 41(2), pp. 14-25.

Polat, S., Aksoy, A., & Unlu, K. (2015). A Fuzzy Rule Based Remedial Priority Ranking System for Contaminated Sites. *Groundwater*, *53*(2), pp. 317-327.

Pujawan, N. I., & Geraldin, L. H. (2009). House of risk: a model for proactive supply chain risk management. *Business Process Management Journal*, *15*(6), pp. 953-967.

Rodrigue, J.P. (2017). *The Geography of Transport Systems*, Fourth Edition, New York: Routledge.

Ross, T. J. (2009). *Fuzzy logic with engineering applications*. New Jersey: John Wiley & Sons.

UNCTAD, (2017). *Review of Maritime Transport*. New York and Geneva: United Nations Conference on Trade and Development.

Vidyarthi, N., Celebi, E., Elhedhli, S. & Jewkes, E. (2007) Integrated production-inventory-distribution system design with risk pooling: Model formulation and heuristic solution. *Transportation Science*, 41(3), pp. 392-408.

Vilko, J.P.P., and Hallikas, J.M. (2012) Risk assessment in multimodal supply chains. *International Journal of Production Economics*, 140(2), pp.586-595.

Vilko, J.P.P., Ritala, P. and Hallikas, J.M. (2016) Risk management abilities in multimodal maritime supply chains: Visibility and control perspectives. *Accident Analysis & Prevention*. https://doi.org/10.1016/j.aap.2016.11.010

Wan, C., Yan, X., Zhang, D., Shi, J., Fu, S., & Ng, A. K. Y. (2015). Emerging LNG-fueled ships in the Chinese shipping industry: a hybrid analysis on its prospects. *WMU Journal of Maritime Affairs, 14*(1), pp. 43-59.

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

Wang, H., Tan, J., Guo, S. & Wang, S. (2018). High-value transportation disruption risk management: shipment insurance with declared value. *Transportation Research Part E: Logistics and Transportation Review, 109*, 293-310.

Wang, J., Yang, J. B., & Sen, P. (1995). Safety analysis and synthesis using fuzzy sets and evidential reasoning. *Reliability Engineering & System Safety, 47*(2), pp. 103-118.

Wang, Y. M., Yang, L. H., Chang, L. L., & Fu, Y.G. (2014). Rough set method for rule reduction in belief rule base. *Control & Decision*, 29(11), 1943-1950.

Willis, O. (2011). UK to allow armed guards on their merchant ships. News, Published on Thu, November 10th. Accessible at: https://www.standardmedia.co.ke/article/2000046457/uk-to-allow-armed-guards-on-their-merchant-ships

Wu, B., Yan, X., Yip, T. L., & Wang, Y. (2017). A flexible decision-support solution for intervention measures of grounded ships in the Yangtze River. *Ocean Engineering*, *141*, pp. 237-248.

Yang, L. H., Wang, Y. M., & Fu, Y. G. (2018). A consistency analysis-based rule activation method for extended belief-rule-based systems. *Information Sciences*, 445, pp. 50-65.

Yang, J. B., Liu, J., Wang, J., Sii, H. S., & Wang, H. W. (2006). Belief rule-base inference methodology using the evidential reasoning approach-RIMER. *IEEE Transactions on Systems Man & Cybernetics Part A Systems & Humans, 36*(2), pp. 266-285.

Yang, J. B., Liu, J., Xu, D. L., Wang, J., & Wang, H. (2007). Optimization models for training belief-rule-based systems. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 37*(4), pp. 569-585.

Yang, Z., Bonsall, S., & Wang, J. (2008). Fuzzy rule-based Bayesian reasoning approach for prioritization of failures in FMEA. *IEEE Transactions on Reliability*, *57*(3), pp. 517-528.

Yang, Z., & Wang, J. (2015). Use of fuzzy risk assessment in FMEA of offshore engineering systems. *Ocean Engineering*, 95, 195-204.

Yang, Z., Wang, J., Bonsall, S., & Fang, Q. (2009). Use of fuzzy evidential reasoning in maritime security assessment. *Risk Analysis, 29*(1), pp. 95-120.

Yang Z., Ng A., Lee P.T.W., Wang T., Qu Z., Rodrigues V. S., Pettit S., Harris I., Zhang D. and Lau Y. T. (2017). Risk and cost evaluation of port adaptation measures to climate change impacts. *Transportation Research Part D: Transport and Environment,* 61(B), 444-458.

Yang Z., Ng A.K.Y. and Wang J. (2014). Incorporating quantitative risk analysis in port facility security assessment. *Transportation Research Part A: Policy and Practice*, *59*, pp. 72-90.

Yang, Z., Yang, Z., Yin, J. & Qu, Z. (2018). A risk-based game model for rational inspections in port state control. *Transportation Research Part E: Logistics and Transportation Review, 118*, 477-495.

Zhang, D., Yan, X., Zhang, J., Yang, Z., & Wang, J. (2016). Use of fuzzy rule-based evidential reasoning approach in the navigational risk assessment of inland waterway transportation systems. *Safety Science*, *82*, pp. 352-360.

Zhou, Z. J., Hu, C. H., Yang, J. B., Xu, D. L., & Zhou, D. H. (2009). Online updating belief rule based system for pipeline leak detection under expert intervention. *Expert Systems with Applications, 36*(4), pp. 7700-7709.